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EVALUATION OF MARITIME OPERATIONAL THREAT RESPONSE FORCES FOR THE PACIFIC COAST THEATER

by

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March 2009

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Maritime Intercept Operations in defense of the Pacific Coast Ports are resource intensive. A maritime threat scenario, analytical models, and simulations are used to measure risk to a port given various levels of resource and intelligence. The scenario starts with intelligence that a large commercial ship arriving to a Pacific Coast Port within a 96-hour window poses a security risk. Intelligence further limits the set of threat ships to a subset of all traffic entering a specific port. A limited number of Maritime Operational Threat Response (MOTR) forces are available to detect, classify, and intercept the threat ship before it reaches port. In the first scenario, all ships are boarded before entering port, and impact is measured by delay of ships into port. In the other scenarios, intercept ships are routed to suspect ships and risk measured by the fraction of suspect ships that proceed to port unboarded because of lack of MOTR and surveillance assets. The results show current Coast Guard force structure is not sufficient to protect the Pacific Coast Ports against unspecific security threats without additional assets from the MOTR stakeholders or increased intelligence to limit the target set.

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EVALUATION OF MARITIME OPERATIONAL THREAT RESPONSE FORCES FOR THE PACIFIC COAST THEATER

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ABSTRACT

Maritime Intercept Operations in defense of the Pacific Coast Ports are resource intensive. A maritime threat scenario, analytical models, and simulations are used to measure risk to a port given various levels of resource and intelligence. The scenario starts with intelligence that a large commercial ship arriving to a Pacific Coast Port within a 96-hour window poses a security risk. Intelligence further limits the set of threat ships to a subset of all traffic entering a specific port. A limited number of Maritime Operational Threat Response (MOTR) forces are available to detect, classify, and intercept the threat ship before it reaches port. In the first scenario, all ships are boarded before entering port, and impact is measured by delay of ships into port. In the other scenarios, intercept ships are routed to suspect ships and risk measured by the fraction of suspect ships that proceed to port unboarded because of lack of MOTR and surveillance assets. The results show current Coast Guard force structure is not sufficient to protect the Pacific Coast Ports against unspecific security threats without additional assets from the MOTR stakeholders or increased intelligence to limit the target set.

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EXECUTIVE SUMMARY

Thousands of ships visit United States Pacific Ocean ports each year. The Pacific Coast ship-port system is responsible for goods and services exchange, which contributes, to approximately 11% of the U.S. Gross Domestic Product. The ports also represent a vulnerability that is exploitable by terrorist or criminal organizations that intend to attack the U.S. infrastructure, security, and economy. Such a threat has been recognized, and has led to the creation of the Maritime Operational Threat Response Forces Requirements (MOTR) Document. The United States West Coast Port System has six major ports handling approximately 88.9% of the total coast tonnage and 99.5% of the Containerized cargo on the West Coast. The Ports of Seattle/ Tacoma, Washington; San Francisco Bay Ports, California; Columbia River Ports, Oregon/Washington; and Los Angeles/ Long Beach, California represent the major ports on the West Coast. These ports each have only one distinct traffic chokepoint or channels through which all vessels entering the port pass.

In this thesis scenario, an intelligence report has been received of at least one large commercial ship threat arriving to the U.S. Pacific Coast Ports within 96 hours. Intelligence further limits the set of threat ships to a subset of all traffic entering a specific port with a specific characteristic for example: Last Port of Call; this subset is called the target set. A limited number of Maritime Operational Threat Response (MOTR) forces are available to detect, classify, and intercept the threat ships before they reach port. Risk is modeled by considering three different scenarios. In the first scenario, all ships are boarded and the port traffic is delayed until ships are inspected. The measure of effectiveness (MOE) is the average ship delay due to boarding, and the wait to be boarded. In the next scenarios, intercept ships are routed to suspect ships and risk is measured by the fraction of suspect ships that proceed to port unboarded because of lack of MOTR and surveillance assets. In the second scenario, every ship is identified without error by overhead Automatic Identification System (AIS) sensor and intercept ships are routed to a ship in the target set; a target ship can proceed to port unboarded if all assets are busy during its transit. In the third scenario every ship must be identified by personnel operating an aircraft before it is boarded by an intercept ship; a target ship can be missed

by being misclassified by the aircraft personnel or if all assets are busy while it transits through the operating area of the intercept ships and aircraft. In the second and third scenario, the MOE is the fraction of ships in the target set that proceed to the port unboarded.

Analytical and simulation models represent the three scenarios. Simulation models can represent additional features more readily than the analytical models. Data from additional simulations are used to estimate parameters of reasonable distributions for the random time a ship transits the operating area, the time required for aircraft to find and identify a ship, and the random time a boarding and search process requires. The MOEs for the analytical models are long run averages, which are then compared to the simulation results. The analytical models provide reasonable approximations to the simulation results for the scenario MOEs in all cases. The analytical models provide key bounding results for the simulations.

The results of the thesis suggest that USCG assets used for maritime intercept operations are not sufficient to protect the West Coast Port System from an unspecific incoming large ship threats. Other MOTR stakeholders are required to support USCG forces in this type of operation. The USCG requires additional surface ship assets in all port areas or increased intelligence sharing to reduce the target set of ships of interest so current USCG ships and their organic air assets can successfully complete this maritime interception operation (MIO). The need for high-endurance air assets with long on-station times and the ability to be directed by sea or land assets is critical to this operation, since the ability of aircraft to identify and classify all traffic limits the number of MOTR assets needed to complete the MIOs. The capability to identify the accurate subset correctly which consist of ships of interest prior to the operation and the correct classification of all ships using aerial vehicles during the mission is critical to reduce MOTR surface asset participation. Specific training of personnel and procurement of search equipment is also required to reduce the number of surface assets necessary to complete these missions. Lastly, ship traffic and the size of vessels to the U.S. coastal ports continue to grow. Hence, enemy exploitation of incoming ships to U.S. ports continues to represent a vulnerability to the U.S. economy and citizens. This thesis underlies the need for accurate and timely intelligence sharing, flexibility in asset cooperation amongst stakeholders, and the ability to execute a joint/ interagency operation in a short time.

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I. INTRODUCTION

A. BACKGROUND

Thousands of ships visit United States Pacific Ocean ports each year; the ship-port system is responsible for goods and services exchange, which contributes, to approximately 11% of the U.S. Gross Domestic Product (PMA, 2007). The ports also represent a vulnerability that is exploitable by terrorist or criminal organizations that intend to attack the U.S. infrastructure, security, and economy. Such a threat has been recognized, and has led to the creation of the Maritime Operational Threat Response Forces Requirements (MOTR) Document (DHS, 2007). The MOTR facilitates an information and force-sharing network to protect ports along the Atlantic, Pacific, and Gulf of Mexico. The specific threats of smuggling entities such as weapons, terrorist personnel, and goods, or use of a lethal ship as a weapon, are identified as key threats to the U.S. homeland.

The United States West Coast Port System has six major ports handling approximately 88.9% of the total coast tonnage and 99.5% of the containerized cargo arriving to the West Coast (PMA, 2007). The Ports of Seattle/ Tacoma, Washington; San Francisco Bay, California; Columbia River, Oregon/Washington; and Los Angeles/ Long Beach, California represent the major ports on the West Coast. These ports each have only one distinct traffic chokepoint or channel through which all vessels entering the port pass. These chokepoints represent major vulnerabilities in the ability of the U.S. to process cargo. In 2007, the West Coast Ports moved approximately 370 million tons of cargo through the ports, and the ports employed 15,000 people generating $1.41 billion dollars in the port system alone. The Pacific Maritime Association also estimates that the West Coast ports support 8 million U.S. jobs across the United States, making the system critical to the economy of the United States (PMA, 2007).

The threat to maritime domain and port systems has increased in the last eight years, exemplified by the attacks on *USS Cole (DDG 67)* in Yemen, the French *M/V Limburg* in the Bab el Mandeb, and the attacks against the Iraqi Oil Terminals in the

Northern Arabian Sea (DHS 2007). The potential for terrorists to use ships as weapons for dramatic effects is a significant threat. Another threat associated with the ports is the potential for terrorist and criminal groups to use the high volume of cargo and containers at U.S. ports to disguise weapons and illegal supplies shipments among legitimate cargo. These illicit cargoes could then be used against U.S. citizens. Thus, the ports are a major target for any organization planning attacks on the U.S. Mindful of this growing threat the President of the United States signed the MOTR Plan in October 2005, to create an intelligence and operational organization designed to protect the maritime ports.

The MOTR document describes a defense plan focused on echelon defense; the first echelon is composed of the forces deployed offshore to prevent threatening enemy craft from entering territorial waters. The second echelon focuses on Port Security and the forces on land to oppose threats. A third echelon force focuses on WMD and the "gravest" threats in the Maritime Theater (DHS 2007). Interagency cooperation and an integrated plan of defense of the U.S. ports is a new area of focus for the Department of Homeland Security.

Previous work on assessing numbers and types of assets needed for the Port and Shipping Defense mission includes the Naval Postgraduate School Master of Science thesis by Kim Chuan Chng, (Chng, 2007). This thesis considers traffic in congested strait and port and considers a combination of aerial vehicles and ships to guard the strait from multiple small boat attacks. Chng's work is used to help frame scenarios and suggest models to relate to the scenarios along the West Coast of the United States. Another related work is the Naval Postgraduate School Master of Science thesis by Edward Pidgeon (Pidgeon, 2008). This work is primarily focused on the port aspects of the MOTR plan, where the risk associated with closing an individual port would affect the shipping network. Other work done by Sato, Jacobs and Gaver on the topic of homeland defense considers models to assess force structures required for the mission (Gaver, 2009). The paper based on the Master's Thesis by Sato is useful in identifying similarities and differences in various Homeland Defense scenarios (Gaver, 2009).

This thesis focuses on the blue water defense of U.S. ports before the invading target ship can physically close ports and rail hubs. It differs from previous work by

including multiple Red targets and allowing air platforms to continue to search rather than escort ships to the surface units. The work provides a risk assessment of U.S. ports, and provides force structures to minimize the effect of dangerous shipping to the specific port structure.

B. OPERATIONAL SCENARIO

The general scenario for the thesis involves an unidentified large ship over 300 tons carrying a deadly cargo to a U.S. Port. The cargo was loaded without knowledge of the crew and hidden within legitimate cargo. U.S. intelligence has received a report that the ship is scheduled to arrive at a U.S. port within 96 hours of a certain date. The ship and crew comply with U.S. instructions, and the U.S. Department of Homeland Security (DHS) decides to find, board, and stop the vessel outside of U.S. territorial waters but within the U.S. Economic Exclusive Zone (within 200nm of the coastline). The DHS directs the use of a variety of different assets based at the port. Risk and operational availability of Blue intercept platforms limit the closure time of the West Coast ports while ensuring their safety.

C. THESIS OBJECTIVE

The objective of this thesis is to evaluate the current force structure, and to identify areas in which to improve force structure to intercept and board a suspect ship prior to its entering a U.S. port on the West Coast. Two separate models are used to establish upper and lower bounds on resource requirements based on the fidelity of threat intelligence. A third more elaborate model that takes into account some of the complexity of current intelligence capabilities is used to recommend the proper force mix to complete the operation. The first scenario (Upper Bound) considers the number of assets required to board and investigate all ships over 300 tons entering the ports. This model establishes an upper bound on forces needed to implement a worst-case scenario, in the case in which no specific intelligence concerning the threat is available. The second scenario uses the premise that long-range surveillance aircraft are able to give intercept units correct information on the identity of all shipping targets. These aircraft are able to pass the location and identities of ships belonging to the collection of ships of interest,

e.g., are part of the target set for boarding and searching. This model establishes a lower bound or "best-case" intelligence scenario for the intercept forces. In this case, the U.S. Forces have the ability to exploit Automated Information System (AIS) and other long-range intelligence gathering techniques to limit the target set (Department of Homeland Security, 2009). Lastly, a third scenario is considered that is based on current or near-term capabilities of the MOTR first echelon forces, to search, identify, and intercept cargo ships based on intelligence, aircraft, and USCG cutters on the West Coast. This third scenario is created to explore the issue of force requirements, force mix, and risk to the ports. This scenario includes both long and short-range aircraft and the difficulty of identifying targets at sea and the imperfect interception of these selected targets. The model for this last scenario is used to recommend force requirements and force mix.

D. RESEARCH QUESTION

In response to the MOTR plan, a limited set of U.S. assets is available to patrol, intercept, and interdict enemy ships threatening to the United States. Mathematical/ analytical models and process simulation software are used to evaluate Measures of Effectiveness (MOEs) and gain further insight into the force structure needed for Maritime Interdiction Operation (MIO) for port defense.

The scenario contains multiple single large container/cargo ships (over 300 tons) traveling to a U.S. Port(s) from the Pacific Ocean. Among these vessels, only limited intelligence is available about the threat, such as that the target is in a certain subset of ships; for example, type of ship (i.e., Group 3), Last Port of Call, and flag of registering country (i.e., Panama). The approximate time, within 96 hours, of the ship's actual arrival is assumed known. These assumptions limit consideration of ship and aircraft maintenance and availability once the operation starts. It is assumed that the ship operators are unaware that a ship is carrying the lethal threat cargo, and do not actively avoid MOTR assets; however, the search teams know the nature of the target cargo. The scenario focuses on the assets required to find and interdict such a ship before it can reach U.S. Inland Waters.

The asset list for the U.S. team is the units assigned to OPERATION NOBLE EAGLE including those of the Department of Defense and the Department of Homeland Security. These assets are representative platforms (i.e., USN DDG-51, USCG WHEC/WMEC) to be used in the model to represent real assets along the Pacific Coast. Additional overhead assets from all agencies that can be used to support search and classification efforts are also included. The study focuses on present and planned force allocations in Pacific Coast Region, for example those Coast Guard Districts 11 and 13, and USNORTHCOM assets in the Pacific theater.

The model evaluates the risk versus reward of different operational scenarios, force structures, and force mix for the defense of the West Coast Ports. The study focuses on the effects of creating an integrated maritime picture where ships are classified as friendly (by AIS or similar system) or as suspicious in order to aid the Blue search and interdiction units.

E. SCOPE OF THESIS

This thesis focuses on the three major scenarios described above. Both mathematical and simulation models are developed for all scenarios. The mathematical models are used to explore Measures of Effectiveness quickly as a function of hypothetical parameters under specified distributional assumptions. The simulations are more readily flexible to change the features of the scenarios to provide insight into risk and flexibility for the defenders under more general model assumptions.

First, the Upper Bound or Minimal Intelligence-100% Boarding Scenario using mathematical/analytical models and the Arena simulation software, is used to assess the time required to board all ships bound for the four key port zones in the West Coast. These models should consider the “worst case” of a minimal intelligence scenario. This scenario causes the assets to board and search all inbound large ship traffic in an approximately 96-hour period to the six largest ports in the West Coast. The MOE is the Average delay of traffic into port based on the Maritime Interdiction Operations (MIO) operations outside the approaches to the port.

Second, the Lower Bound or Good Intelligence-Targeted Boarding Scenario using mathematical/analytical models and the Arena simulation software is used to assess the ability of defenders to board and search Red Targets with the "best-case" or perfect intelligence to identify a ship carrying hazardous cargo (Red shipping) in a specified subset of ships among normal innocuous ships (White shipping). In this model, a long-range surveillance aircraft using an AIS-like system can pass all required information to intercept units in the four critical port zones. These models should establish a lower bound on the number of assets needed to board a certain percentage (narrowed by intelligence) of the traffic into the six major ports. The MOE is the Miss Rate or the fraction of ships in the target set not intercepted by MOTR assets.

Lastly, the General Model or Imperfect Information-Targeted Boarding Scenario using Arena simulation software and Mathematical models, explores the operations of the units using long and short-range aircraft to detect and identify traffic. The identification of traffic can be erroneous in this scenario. The MOE is the Miss Rate or the fraction of ships in the target set not intercepted by MOTR assets. This model outputs operational level planning for defense of the Pacific Coast Theater.

F. THESIS MAP

The remaining thesis exposition is structured in the following chapters.

Chapter II presents detailed descriptions of the Concept of Operations and Scenarios for all models.

Chapter III explores the sensitivity of model MOEs to model parameters and distributional assumptions. The choice of distributions for the simulation model is also discussed.

Chapter IV presents a comparison of the Mathematical and Analytical models developed for the scenario, and provides recommendations on current and projected force structure.

Chapter V presents the quantitative results for the mathematical and simulation models.

Chapter VI presents a summary of the results, conclusions, and recommendations for further work.

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II. MODEL DESCRIPTION

A. GLOBAL PARAMETERS

All three scenarios have similar values for a few key variables. The arrival rate of the ships into the ports is based on the number of Vessel Calls in the year 2007, as published by U.S. Department of Transportation (USDOT), which compiled the data from the Lloyds Maritime Intelligence Division (U.S. Department of Transportation, 2009). The number of ships in and out of ports varies with the season, weather, and economics; however these features are neglected, here, and the average arrival rate over the year is used as a basis for further analysis. The arrival of ships to a port is assumed to occur according to a time-homogeneous Poisson Process. The e*xponential distribution* was chosen for the ship inter-arrival times because of the apparent independence of ships arriving at port and the significant number of factors affecting arriving ships. These factors include variations in environmental factors, scheduling, and transit delays experienced by ships traveling trans-oceanic routes. The arrival rates listed below in Table 1 are derived from 2007 Vessel Calls at each port from USDOT. The next input is the number of Maritime Interdiction Operations (MIO) surface vessel assets at each port, which is based on February 2009 data of homeports of U.S. Coast Guard WHEC, NSC, and WMEC class cutters. These assets have the ability to carry organic aircraft or these ships have facilities to land, fuel, and service aircraft, on the West Coast (United States Coast Guard, 2009). Smaller vessels such as WPB and WPC class vessels are not considered due to the requirement for an organic aircraft for the MIO mission and the likely necessity to continue normal Coast Guard operation in these areas. These smaller vessels would also be likely candidates to intercept the targets that make it through the MIO operations discussed below. The input values for arrival rates of ships arriving to the ports and the numbers of WMEC and WHEC class cutters are listed below in Table 1. These are varied in later sensitivity analysis. Table 1 values provide the base case for each scenario. Since the number of MIO surface assets varies, they are referred to as MOTR assets. Other MOTR stakeholders such as the U.S. Navy may provide surface vessels with organic air assets to complete the mission.

For the Good Information-Targeted Boarding and Imperfect Information-Targeted Boarding scenarios an exponentially distributed random time of one hour is used to represent the time a MOTR surface asset takes to intercept a potential target ship prior to boarding. The exponential distribution is chosen for its convenient memoryless/ Markov property. The MOTR asset and target ship could be located anywhere in the operational area, but the target ship has known area of travel. One hour is chosen as an average time based on the size of the area and likelihood that MOTR assets migrate towards the west or port side of the operations area as the MIO continues and the target ships have a known destination to the port. This intercept time appears in most analytical and simulation models and is conventionally an independent exponentially distributed random variable here with mean one hour.

The last common parameter in all scenarios is the boarding and search time, which is the time the interceptor vessel, is busy boarding and searching the target ship. This process is based on current U.S. Navy and U.S. Coast Guard tactics for VBSS (Visit, Board, Search, and Seizure), where the interceptor vessel stays with the intercepted ship and boarding team(s) until the Boarding/Search of the target ship is complete. The actual process of searching the ship and tactics for the search are not a primary recommendation of this analysis; instead, these times have an assumed distribution in the analysis. The specific distribution for the typical VBSS time is discussed in detail in Chapter III. Other variables, such as the times the Target Ships are in the Operating Area, the classification rates, and the percentage of Traffic containing ships of interest are discussed in detail for each scenario.

Port Zone	**Arrival Rate (ships / hr) [λ]**	**Mean Inter-Arrival Time (Hours) [1/λ]**	**MOTR Assets**
Seattle-Tacoma	0.27	3.7	3
Columbia River	0.29	3.4	2
San Francisco Bay	0.45	2.2	3
Los Angeles-Long Beach	0.63	1.6	4

Table 1 List of Scenario Common Data

B. MINIMAL INTELLIGENCE CASE-100% INSPECTION

1. Concept of Operations

In the "Minimal Intelligence" case, all ships of a particular size must be boarded and searched. It is assumed that there is no intelligence to focus the search on a subset of the population of ships or target set. This case does not allow targets to pass into port without inspection by a MOTR surface asset, called an interceptor. In this case, targets enter the port zone, and stop in a designated boarding area(s) (outside the port) and wait for an interceptor to approach and board the target. A simple line drawing is displayed below in Figure 1 to illustrate the scenario; scenario variables are shown in Red. In this scenario no aerial vehicles are needed and scenario specific variables are the variable time to board/search the targets (VBSS time), and the "work-day" or physical time Board and Search can take place. In the simulation model, the "work-day" is represented as a parameter, which limits the number of hours per day the boarding teams are utilized.

The Scenario Measures of Effectiveness (MOEs) are the time a ship is in Queue (waiting for a boarding party); the number of ships in the Queue; and the Boarding Team Utilization Factor (the percentage of time the boarding team is searching). The time in Queue and the number in Queue measure the delay of traffic to the ports due to the preventive operations. Since there is minimal risk of a hostile ship reaching port, if the search teams are effective, there is no mitigation in this scenario. Instead, these MOEs determine the economic impact of delaying entrance of ships to the ports while boarding operations are conducted. In the simulation model, the boarding teams can only board ships during part of a day; in the analytical model, boarding teams can board 24 hours per day. The simulation workday can be adjusted for model comparison or different operational consideration including weather and high-level tasking of assets. The percentage of time the boarding team is busy is primarily a usage percentage of the Boarding Teams in the Simulation.

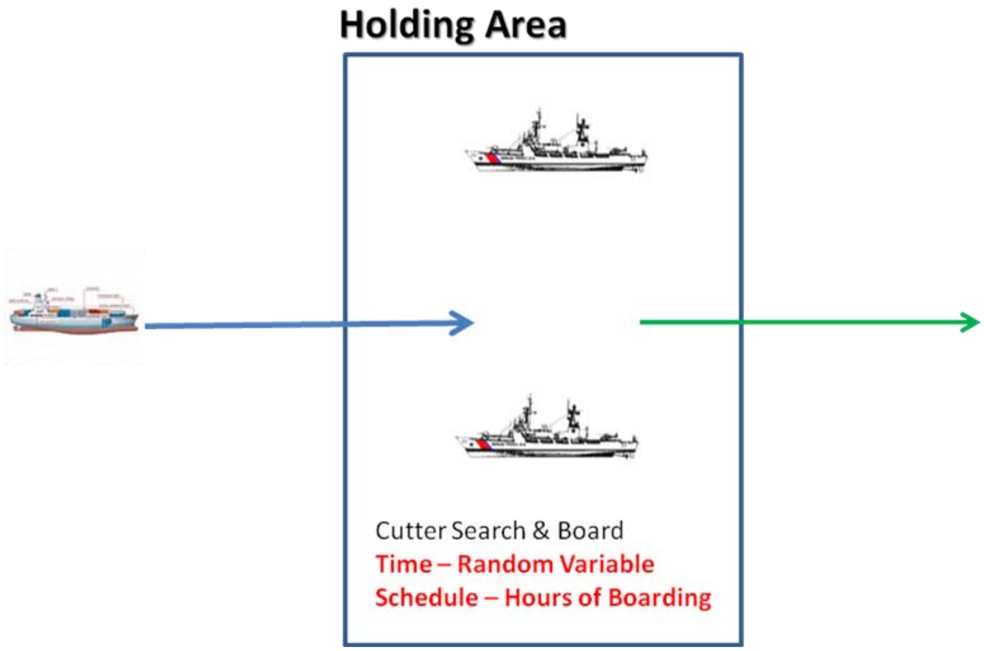

Figure 1 Line Drawing of Minimal Information-100% Boarding Case

2. Minimal Information-100% Inspection: Mathematical Model (I)

The mathematical model for this case is developed from a multiple server queuing model with an infinite waiting room; the queue is processed according to a First Come – First Serve discipline (FIFO). This model is discussed in detail in Appendix A. The Measures of Effectiveness are when conditions permit, the long run Average Number of Ships in Queue and the long run average Waiting Times; these values are recorded to obtain how much delay a representative ship experiences waiting for boarding before proceeding to the port. This model and the methodology provide an approximation to the general case, which is described and simulated in the next section.

3. Minimal Information-100% Inspection: Simulation Model (II)

The Upper Bound Scenario simulation is built in the Arena Modeling Software Tool developed by Rockwell Software and is described in detail in Appendix B (Rockwell Software Inc., 2005). In the simulation, the boarding team has a designated workday of 14 hours, but if there is a boarding/search operation ongoing at the end of the workday, the team finishes the current operation before stopping for the day. The

Measures of Effectiveness (MOEs) for the simulation is the Average Total Delay of the ships. The Average Total Delay for the ship gives the amount of time the ships are delayed while waiting for a boarding team, and the boarding process, prior to entering port. For MOE calculation, all ships that arrive and leave during the first 96 hours are computed, so that is ships that have not completed inspection at the end of 96 hours are not counted.

C. GOOD INFORMATION-TARGETED BOARDING CASE

1. Concept of Operations

The Perfect Information case includes a high Altitude aircraft or UAV with the ability to detect and classify all tracks as they enter the operating area. The operating area for the final two cases is defined as a 200 nm by 100 nm box, outside of territorial waters at the entrance to the ports. In this case, there is a "perfect" AIS environment: all large ships are assumed to use this system and report the correct information. Ships arrive to the operating area and continue to the port unless stopped by an interceptor. Prior intelligence has limited the ship(s) carrying the illegal cargo to a subset of the total traffic. Interceptors only board ships in this target set. The ships in the target set spend a random time in the operating area (based on the size of the detection/classification area and ship speed); a ship can pass on to the port without being stopped if there are no interceptors available to board it while it is in the area. All ships are assumed to be correctly classified as *Suspicious* (in target set) [Red] and *Friendly* (not in target set) [White]; ships are assumed to stop when approached by interceptors. A simple line drawing displayed with scenario variables are shown in red is displayed in Figure 2.

The Scenario MOEs quantify the risk of letting a Red Ship into port without a prior search by an interceptor. The critical measure is the Miss Rate or percentage of the target set (Red Ships) that pass through the region without being boarded. This MOE represents the risk of allowing a dangerous ship into a friendly port as a function of the target set traffic, the boarding time, the number of interceptors, and the size of the operating area.

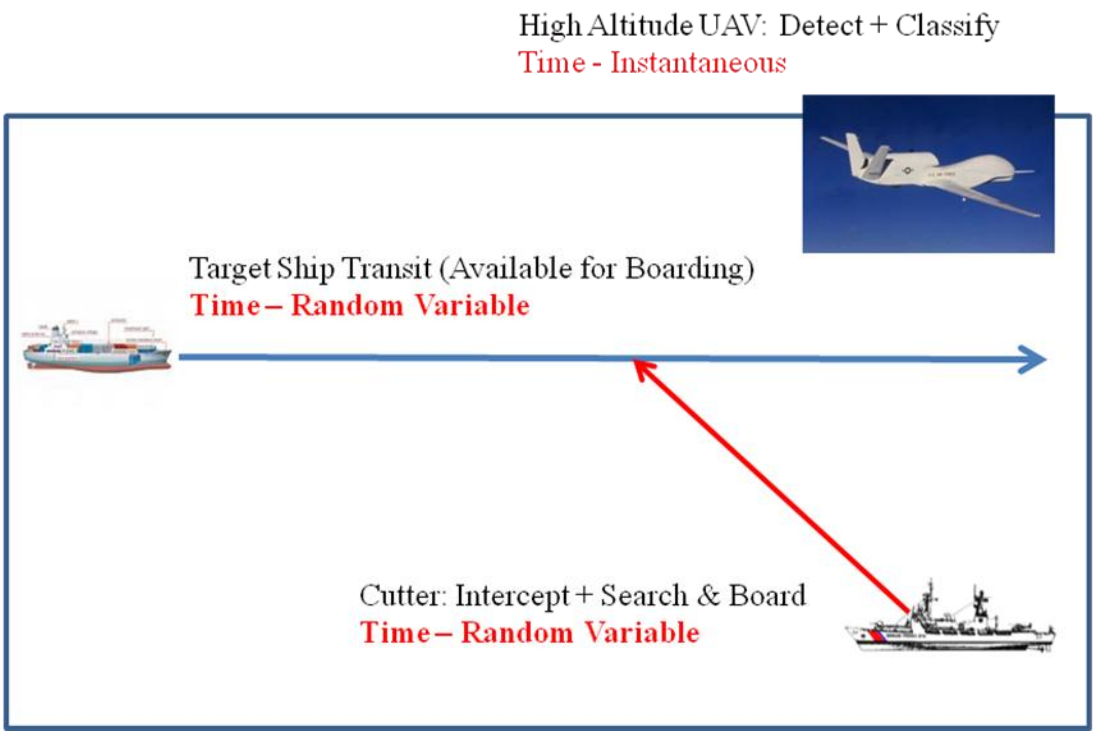

Figure 2 Line Drawing of Good Information-Targeted Boarding Scenario

2. Good Information-Targeted Boarding: Mathematical Model (I)

The Good Information-Intelligent Boarding Analytical Model is based on a Birth Death Model using Continuous Time Markov Chains. The model is described in detail in Appendix A. The critical MOE is the long run average percentage of traffic not intercepted by MOTR assets, which measures the risk to the port.

3. Good Information-Targeted Boarding: Simulation Model (II)

The Lower Bound Scenario simulation is built in the Arena Modeling Software Tool developed by Rockwell Software and is described in detail in Appendix B (Rockwell Software Inc., 2005). Again, the model's key MOE is Miss Rate, where all ships that arrive and leave during the first 96 hours are computed, so that ships that have not completed inspection at the end of 96 hours are not counted.

D. IMPERFECT INFORMATION-TARGETED BOARDING CASE

1. Concept of Operations

The scenario of the general model is similar to that of Section C with the addition of low-altitude aircraft that conduct the classification of targets, and a high-altitude aircraft, which conducts detection of targets only. Prior intelligence restricts the ship carrying illicit lethal cargo to a subset of the ship traffic called the target set. Every target ship is required to be visited by an aircraft before being intercepted by MOTR ships. In this scenario ships still have a finite random time in the operating area (specified by size of the operating area and ship speed). Low-altitude aircraft misclassify some ships, which can allow targets to be missed by being wrongly labeled White (friendly) or vice versa; similarly White ships can be boarded even if they do not fit the intelligence criteria for boarding, but are misclassified. For example, a ship's name or last port of call could be mistakenly transmitted to an aircraft causing the operator to misclassify a ship either red or white. Once the aircraft have classified a ship as belonging to the target set, the ship is handed off to surface interceptors for boarding and search. Since the high-altitude aircraft is keeping track on all ships, low-altitude aircraft are not required to stay with the target ship until intercept; instead, the aircraft continue to the next unidentified ship. It is assumed that no large ships are lost from track. A simple line drawing with scenario variables in Red is displayed below in Figure 3. This scenario requires models for the Aircraft Search and Classify process and the Ship Boarding and Search process, which are described in detail below. This last scenario represents the current tactics of the MOTR forces in the Pacific Coast Theater, and is the primary focus of the analysis sections.

The Measure of Effectiveness for this scenario is the Miss Rate, defined as the number of Red ships not boarded before entering port, based on the total number of Red ships that have entered and left the region in 96 hours. This rate provides the risk to the specific port based on the percentage of Traffic in the target set; the classification probabilities of the low-altitude aircraft; the time the ship is in the operating area; the number of interceptors; and the time interceptors spend conducting boarding operations. The three key outputs of the models to calculate the Miss Rate listed below in Table 2.

These outputs are calculated by all the models to determine Miss Rate. Other Measures of Effectiveness related to low-altitude aircraft are discussed for the individual Search and Detection scenarios.

Output Parameter	Parameter Description
LA	The average number of Red ships that leave the area before being classified by an aerial vehicle
LB	The average number of Red ships that pass through the area without being boarded
LC	The average number of Red ships that are misclassified as White

Table 2 Imperfect Information-Intelligent Boarding Common Modeling Output Parameters

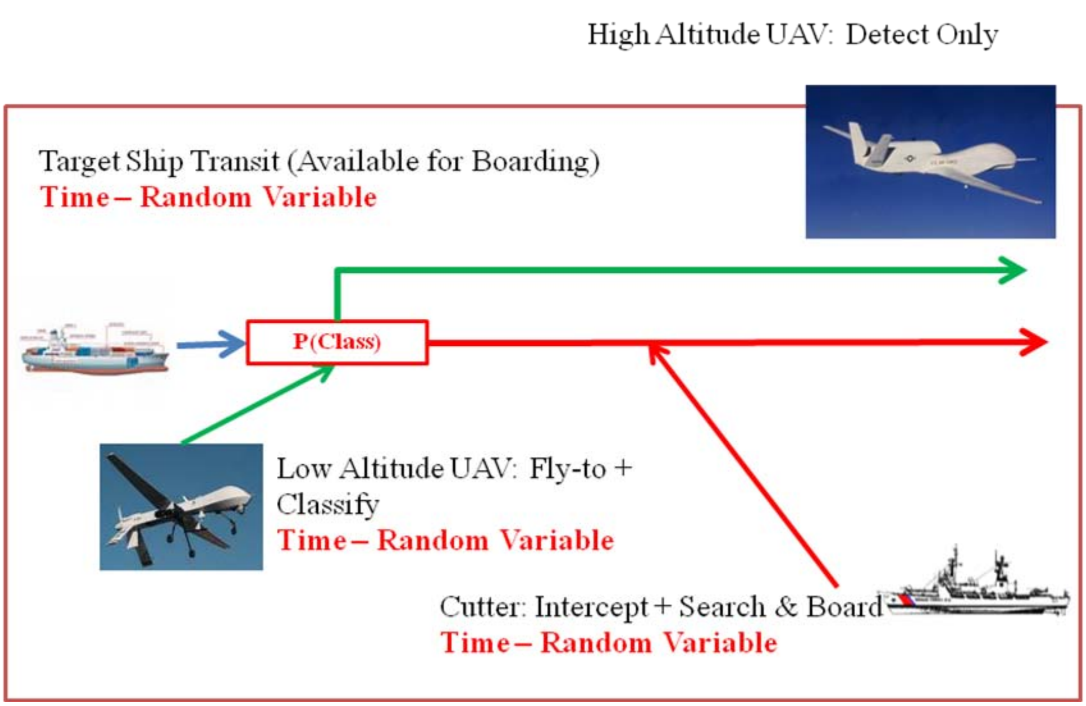

Figure 3 Line Drawing of the Imperfect Information-Targeted Boarding Scenario

2. Imperfect Information-Targeted Boarding: Mathematical Models (I)

Three mathematical models are studied for this scenario. One model, a deterministic Fluid Model, uses a system of differential equations to represent the scenario and results in the common outputs listed above in Table 2. The second model is an approximate M/G/1 Queuing Model with losses based on previous work appearing in *Uncertain Time-Critical Tasking Problem* (Gaver, et al., 2006). The third model is a birth death model similar to the previous section. The Fluid Model provides a lower bound on the Miss Rate, since ships are not processed as whole entities, but as fractions of ships moving in continuous time. The M/G/1 queuing model represents whole ships moving through time. Lastly, the Birth Death Model provides a representation of an undirected random search by aircraft. All three models are described in detail in Appendix A, while the search and detection process is discussed in Chapter III and Appendix C.

3. Imperfect Information-Targeted Boarding Simulation Models (II)

The Simulation is built in the Arena Modeling Software Tool developed by Rockwell Software and is described in detail in Appendix B (Rockwell Software Inc., 2005). The model's key MOEs are described above in Table 2, but other data are collected including average delay at the interceptor queue, and the average number of busy interceptors. These two additional data points give insight into how busy the interceptors are at each port. Also, note the existence of "statistically constant" average delays and busy interceptors only occur when arrival traffic (Red and White) is less intense than the service capabilities.

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III. DISTRIBUTION ANALYSIS

A. METHOD AND DESIGN

In this section, we discuss the choice of the distribution of random times used in the simulations. In the next chapter, the analytical and simulation models are compared using only the exponential distribution for these random times. The distributions of the random times are summarized by parametric distributions. The resulting estimated distributions are then used in the simulations of Chapter V. The Minimal Intelligence-100% Inspection scenario is used to study the effect of the distribution of the boarding and search times on Average Ship Delay. Two targeted boarding scenarios are used to study the effect of the distribution of the Ship Time in Zone on the ability of MOTR assets to intercept target ships. Lastly, the Imperfect Information-Targeted Boarding Case studies the effect of the distribution of Aircraft search and detection time on the number of ships passing through the area without classification by an aircraft. The distributions chosen are used in the simulations performed in Chapter V to study Force structures. Other factors, including Probability of Classification, Number of MOTR Surface Assets, and Number of Aircraft Assets, are discussed in Chapter V. These parameters can be influenced by allocation of MOTR assets to protect U.S. waters.

B. VISIT BOARD AND SEARCH TIME DISTRIBUTION

The Minimal Information-100% Inspection scenario is used to evaluate sensitivity of the MOE Average Ship Delay, on the distribution and distributional moments of the Visit Board and Search (VBSS) times. This particular simulation model is chosen since the MOE is only influenced by Board and Search Times and ship arrival rates. The base case for the VBSS distribution is taken to be the lognormal distribution with mean six and standard deviation two hours; this choice is based on the experience of boarding team participants. Other studies for MIO operations use a mean VBSS time of four hours (service time) for a ship. This thesis also assumes approximately one hour to launch, embark, and evaluate the seaworthiness of the target and one hour to release the crew and safely transit back to the MOTR assets. Six hours is a good approximation for mean

Board and Search time (Grivell, 2008). The lognormal distribution is chosen as a representative right-tail-skewed distribution since boarding team members report that the mean VBSS time is larger than the median. Since the process of boarding and searching could be greatly affected by new technology, differing search goals, or boarding team effectiveness, the effect of three other distributional forms are considered on the MOE of average ship delay. These chosen distributions are listed below in Table 3. For each simulation replication, the average delay, including VBSS time, for all ships that arrive and leave during the first 96 hours is computed. Ships that have not completed inspection at the end of 96 hours are not counted. Figure 4 displays the MOE for the four distributions from the Minimal Intelligence-100% Inspection simulation with a 14-hour workday. The mean is displayed on the horizontal axis and the Average Ship Delay on the vertical axis. The distributions considered in Figure 4 have a constant standard deviation of two hours with the exception of the exponential where the mean is equal to the standard deviation. To create the figures below the port of Seattle-Tacoma arrival rate is used and the port has two boarding teams operating for a 96-hour scenario length. Each VBSS scenario is replicated 500 times for each distribution as to reduce the standard error for the MOE. The Exponential Distribution for VBSS times is also considered to compare the simulation results to those of the limiting analytical model described in Chapter IV. The four lines in Figure 4 represent the four distributions chosen: a Gamma, a Normal with negative values truncated to zero, Exponential, and Lognormal distributions to show the effect of both mean and distribution. Figure 5 displays the MOE case with the mean VBSS time held constant at six hours and the standard deviation of the distribution varied from one to five hours in units of one hour. The MOE for the Gamma distribution is consistently lower than the other three on the graph.

For the distribution parameter values and distributions considered, the MOE is somewhat insensitive to the form of the distribution. It is more sensitive to the mean of the distribution than the standard deviation. Based on this study, the VBSS times are modeled as being drawn independently from a lognormal distribution with mean six

hours and a standard deviation of two hours to keep 95% of the MIOs under 10 hours for crew and operational considerations. However, an exponential distribution may also be adequate and is convenient.

Model Distribution	**Mean Range [Low, High]** **In Steps of 1 hour**	**Standard Deviation Range** **In Steps of 1 hour**
Lognormal	[2,10]	[1,5]
Gamma	[2,10]	[1,5]
Normal	[2,10]	[1,5]
Exponential	[2,10]	[2.10]

Table 3 Model Distributions and Values for VBSS Parameter

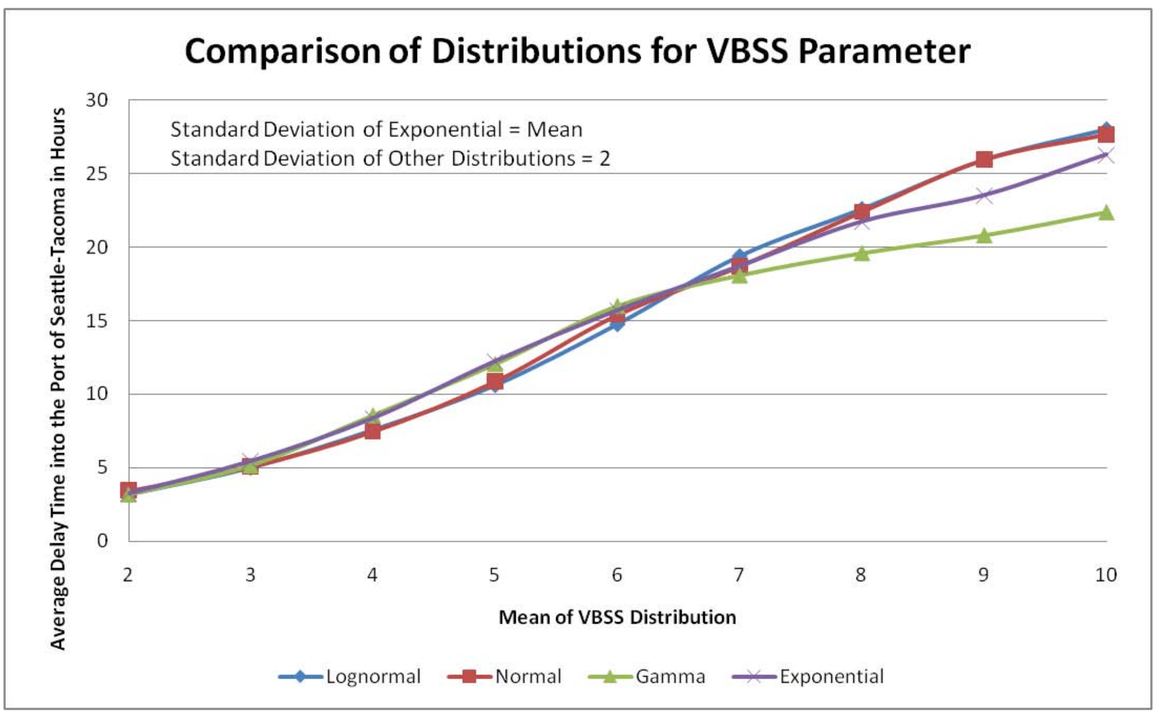

Figure 4 VBSS Parameter Distribution Comparison by Mean

Mean of Distr.	Lognormal Distribution		Gamma Distribution		Normal Distribution		Exponential Distribution	
	Mean (Hrs)	Std Error	Mean (Hrs)	Std Error	Mean (Hrs)	Std Error	Mean (Hrs)	Std Error
2	3.20	0.04	3.18	0.03	3.41	0.03	3.25	0.04
3	5.01	0.07	5.16	0.09	5.07	0.07	5.45	0.10
4	7.58	0.12	8.56	0.18	7.46	0.11	8.37	0.19
5	10.62	0.17	12.05	0.31	10.86	0.18	12.25	0.26
6	14.76	0.23	16.00	0.40	15.40	0.24	15.70	0.34
7	19.39	0.28	18.09	0.45	18.70	0.27	18.71	0.38
8	22.58	0.29	19.60	0.43	22.41	0.30	21.73	0.43
9	25.92	0.28	20.81	0.48	25.96	0.26	23.52	0.43
10	27.99	0.26	22.38	0.54	27.67	0.26	26.29	0.44

Table 4 Means and Standard Errors for Figure 4

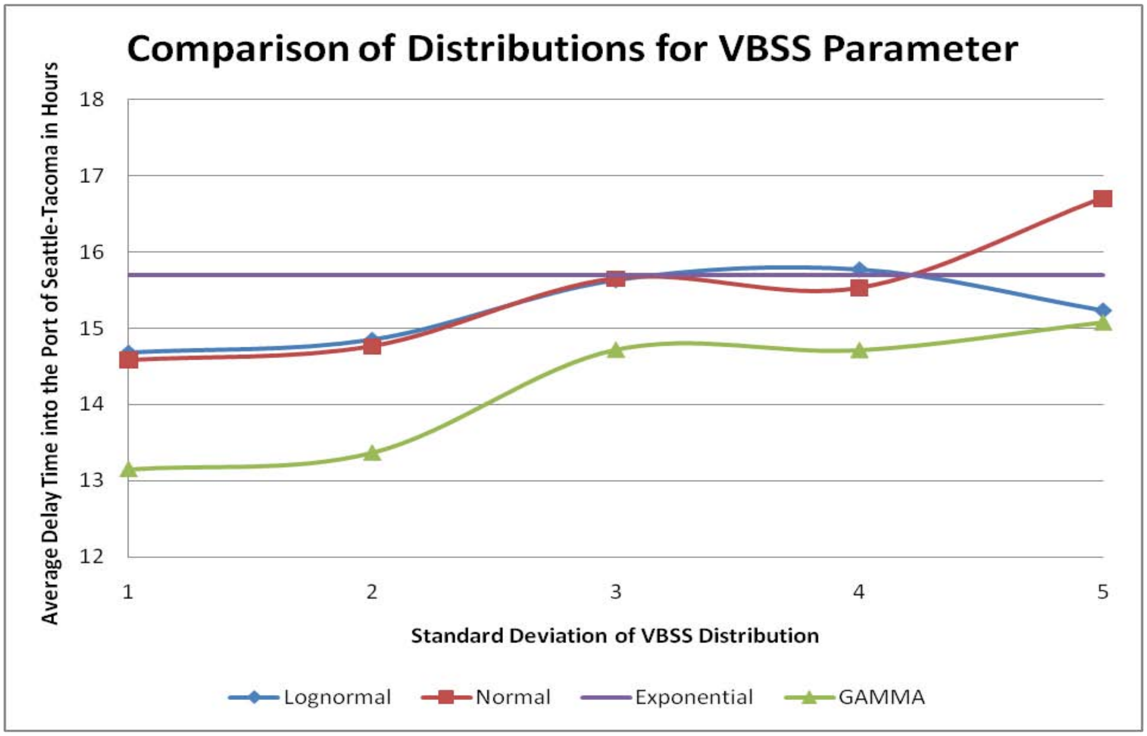

Figure 5 VBSS Parameter Distribution Comparison by Standard Deviation

Std. Dev. of Distr.	Lognormal Distribution		Gamma Distribution		Normal Distribution		Exponential Distribution	
	Mean (Hrs)	Std Error	Mean (Hrs)	Std Error	Mean (Hrs)	Std Error	Mean (Hrs)	Std Error
1	14.68	0.22	13.15	0.45	14.58	0.22	15.70	0.34
2	14.84	0.24	13.37	0.43	14.77	0.23	15.70	0.34
3	15.63	0.28	14.72	0.46	15.65	0.27	15.70	0.34
4	15.77	0.30	14.72	0.46	15.53	0.28	15.70	0.34
5	15.23	0.33	15.08	0.45	16.71	0.29	15.70	0.34

Table 5 Means and Standard Errors for Figure 5

C. TARGET SHIP TIME IN ZONE DISTRIBUTION

To assess the effect of the distribution of the time a ship is in zone on the MOE of Miss Rate (fraction of ships in the target set not intercepted); two simulations are considered. The Good Information-Targeted Boarding Scenario is used to study the no aircraft case and the Imperfect Information-Targeted Boarding scenario is used to study the search with aircraft case. In both cases, the simulation is used to study the effect of the distribution of the time a ship is available to be classified by aircraft, if required, and intercepted by MOTR assets on the MOE, Miss Rate or the fraction of ships in the target set not intercepted.

To estimate the parameters for the distribution of time a ship is subject to detection and search, a small simulation is built to mimic the operational movement of the ships across the area of operations. To obtain a reasonable sized sample, 1000 ship tracks are randomly generated. The ships travel in a 200 nm by 100 nm rectangle starting at the left side and ending on the right side with a constant speed drawn from a uniform distribution between 15 and 30 knots. The time each ship takes to reach the other side of the box is recorded as the output of the model. The ship's destination point on the right side of the box is located more towards the center of the right side of the box to simulate a convergence at the port's Traffic Separation Scheme or Entrance Channel. The ship's destination is drawn from a Normal distribution with mean equal to the center of the right

side and a standard deviation of 10 miles; this distribution forces traffic towards the center. The ship's initial starting position is drawn from a Uniform distribution between the top and bottom of the left side, and each ship starts from the left side. It is assumed that all ships travel independently of each other; the initial ship position, the ship's destination and the ship's speed are independent random variables. The time a ship spends in the region is simulated. Using these generated times parameters for a Beta, Gamma, Normal, and Exponential distribution are estimated using S-Plus Statistical Package (Insightful Corporation, 2007). These parameters for the distributions are chosen based on Method of Moments or Maximum Likelihood estimators of the raw data; for further reading and comparative QQ-plots refer to Appendix C. The individual parameters of the different distributions are displayed in Table 6.

Distribution	**Parameters**	**Equation**
Beta $f(x;\alpha,\beta)=\dfrac{x^{\alpha-1}(1-x)^{\beta-1}}{B(\alpha,\beta)}$ $X=(h-l)*x+l$	$\alpha=0.79$ $\beta=1.31$ $h=13.65$ $l=6.70$	$6.70+6.95*Beta(\alpha,\beta)$
Gamma $f(x;\alpha,\beta)=\dfrac{1}{\beta^{\alpha}\Gamma(\alpha)}x^{\alpha-1}e^{-\frac{x}{\beta}}$	$\alpha=1.84$ $\beta=1.55$	$6.70+Gamma(\alpha,\beta)$
Normal $f(x;\mu,\sigma)=\dfrac{1}{\sigma\sqrt{2\pi}}e^{-\frac{(x-\mu)^2}{(2\sigma)^2}}$	$\mu=9.31$ $\sigma=1.91$	-
Exponential $f(x;\lambda)=\lambda e^{-\lambda x}$	$\lambda=0.11$	-

Table 6 Ship Time in Zone Distribution Parameters

1. No Aircraft

Each of the fitted distribution with parameter listed above in Table 6 is used to generate the time a ship spends in the region in the Good Information-Targeted Boarding simulation. For each simulation replication, the fraction of ships that travel through the region without inspection is computed; ships that entered the region during the 96 hours and are still in the region at the end of 96 hours are not included. Each simulation has 500 replications for the 96-hour scenario. The means and standard errors of the simulations are reported below the figure. Figure 6 displays the MOE of Miss Rate or the fraction of ships in the target set not intercepted as a function of the Number of MOTR Assets assigned to the Port of Los Angeles and Long Beach. The results suggest that for the parameter values considered, the MOE of Miss Rate is insensitive to the form of the Time in Zone distribution since all fitted distribution give nearly identical results. The Beta distribution is used in further work based on the results of the simulation study and the comparative QQ-plots in Appendix C. However, the exponential distribution would also be adequate for the no aircraft case.

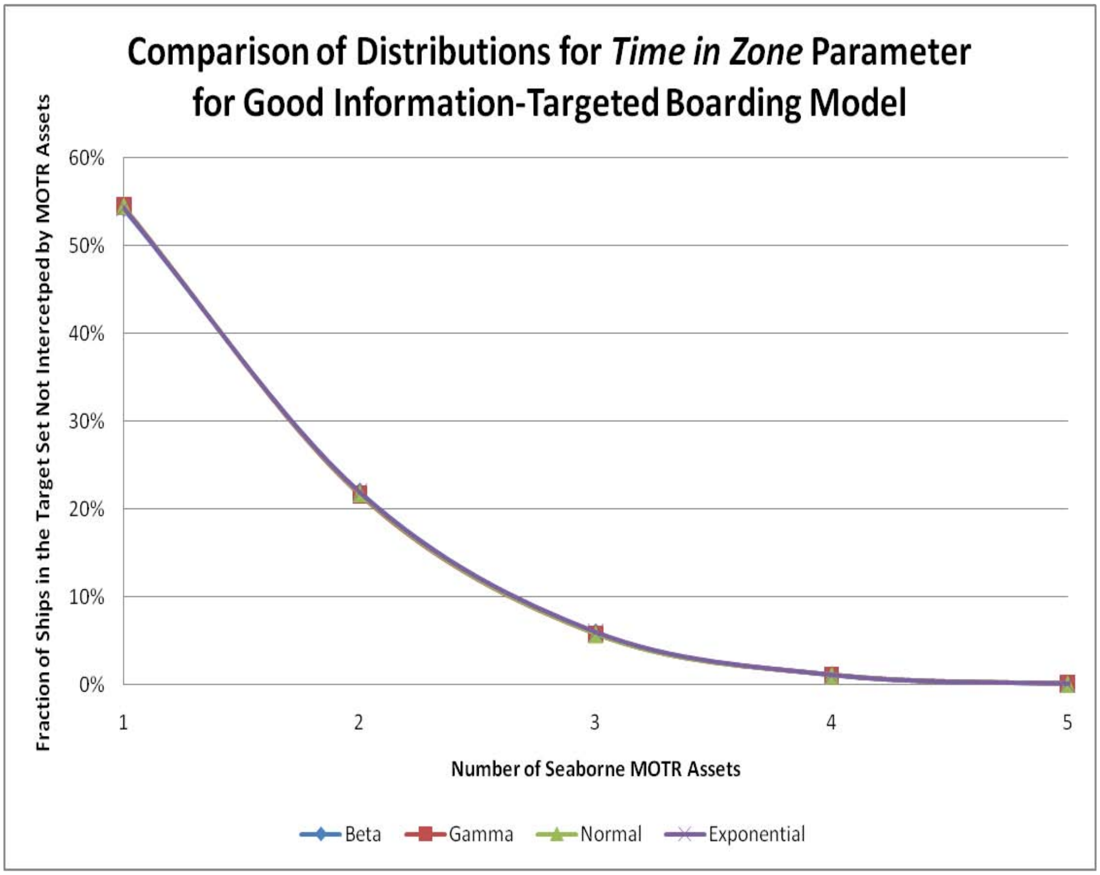

Figure 6 Target Ship Time in Zone Parameter Distribution Comparison for Good Information-Targeted Boarding (No Aircraft) Scenario

Number of Assets	Beta Distribution		Gamma Distribution		Normal Distribution		Exponential Distribution	
	Mean	Std Error	Mean	Std Error	Mean	Std Error	Mean	Std Error
1	0.542	0.003	0.546	0.003	0.545	0.003	0.544	0.003
2	0.220	0.004	0.217	0.004	0.218	0.004	0.219	0.004
3	0.060	0.002	0.058	0.002	0.058	0.002	0.060	0.002
4	0.011	0.001	0.012	0.001	0.012	0.001	0.011	0.001
5	0.002	0.000	0.002	0.000	0.002	0.000	0.001	0.000

Table 7 Means and Standard Errors for Figure 6

2. Aircraft Classification Case

In this case, each of the fitted distributions in Table 6 is used in the Imperfect Information-Targeted Boarding Scenario with finite aircraft. Each simulation has 500 replications using one aircraft in a directed search over a 96-hour scenario and the fraction of the ships that entered but were not boarded during the 96 hours is calculated. Each ship must be classified as Red, or in the target set, using the aircraft prior to possible interdiction. Thus, ships can pass through the region without in inspection in two ways; the ship may not be identified by an aircraft as requiring inspection or the ship may be identified as needing inspection but is not inspected before leaving the region. The means and standard errors of the simulation's MOE are reported below the figure. The aircraft search time has a Uniform Distribution with parameters displayed in Table 12. The aircraft search time distribution is discussed in the next section. The results displayed in Figure 7, suggest that in this case MOE of Miss Rate is sensitive to the distribution of time a ship spends in the region with the exponential distribution having higher MOE results than other three distributions, which have similar results. All of the distributions have the same mean time a ship spends in the region. However, the Exponential distribution has a larger variance that the other three distributions. The increased variance of the exponential apparently causes more losses due to ships not being classified by aircraft. These losses are not affected by increasing MOTR assets since the tracks are never identified as members of the target set for the MOTR assets to board. For this scenario, an exponential distribution for ship time in zone time provides pessimistic or higher results for the MOE with all other inputs similar.

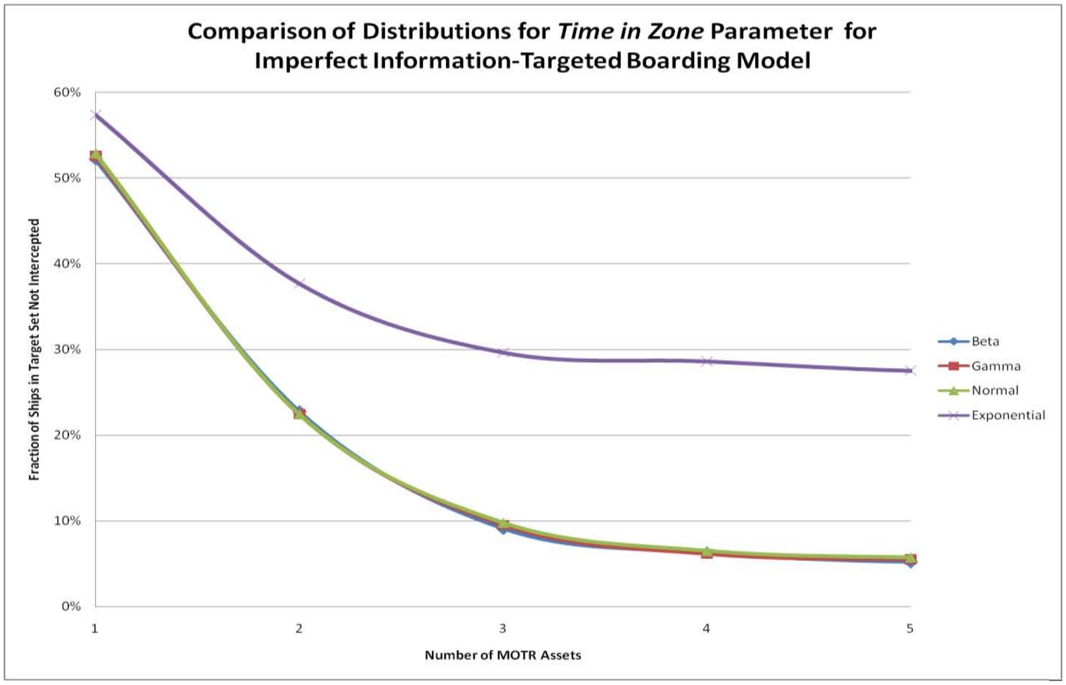

Figure 7 Target Ship Time in Zone Parameter Distribution Comparison for Imperfect Information-Targeted Boarding (Directed Aircraft) Scenario

Number of Assets	**Beta Distribution**		**Gamma Distribution**		**Normal Distribution**		**Exponential Distribution**	
	Mean	Std Error	Mean	Std Error	Mean	Std Error	Mean	Std Error
1	0.522	0.004	0.526	0.004	0.529	0.004	0.574	0.003
2	0.228	0.004	0.225	0.004	0.225	0.004	0.377	0.004
3	0.091	0.003	0.096	0.003	0.098	0.003	0.297	0.004
4	0.063	0.002	0.062	0.002	0.065	0.002	0.286	0.004
5	0.052	0.002	0.055	0.002	0.058	0.002	0.275	0.004

Table 8 Means and Standard Errors for Figure 7

D. AIRCRAFT SEARCH TIME DISTRIBUTIONS

Two aircraft search and detection processes are considered. In the first, an aircraft does an independent search of the area without direction to the targets; in the second, an aircraft travels between unidentified targets based on direction from another source when

a ship to be classified is available. Both search models are described and studied in Appendix C. Simulations of the two processes are used to generate times until aircraft detect ships transiting a rectangle. The distributions of the time are summarized with parametric distributions. The parametric distributions are used in the Imperfect Information-Targeted Boarding Scenario and the MOE of Miss Rate or fraction of ship lost is used to study the differing search strategies, undirected searching aircraft and aircraft directed by the ship or other overhead source between tracks. In this chapter, only low speed organic type assets are used for analysis, in future sections high-speed Maritime Patrol aircraft (MPA) are evaluated.

1. Undirected Searching Low Speed Aircraft

The Undirected Search model is based on a single or multiple aircraft searching an area without knowledge of target location. A simulation of this scenario is built in the JAVA language using non-overlapping ladder search patterns divided evenly in a 200 nm x 100 nm search area, one pattern for each aircraft. The aircraft are assumed to have a search speed of 120 knots and classification sweep width of five nautical miles to replicate small UASs or helicopters conducting a low altitude, unaided visual search. There is one ship crossing the area. The time the ship is detected by an aircraft is recorded; these data may be right censored since the ship may transverse the rectangle before being detected. The censored data collected is used to estimate the parameters of several Weibull distributions for each number of searching aircraft from one to six; the parameters are listed below in Table 9. For details of the process to obtain the parameters of distribution, refer to Appendix C. The resulting estimated Weibull distribution is used as the time for the Aircraft to classify a ship in the Imperfect Information-Targeted Boarding scenario; it is assumed that the classification time in negligible.

In Figure 8 below, the LA MOE (number of ships lost because they were not identified by an aircraft) for the simulation runs is displayed varying the number of Aircraft from one to six for both the Weibull and Exponential Distributions based on the data collected. Each Weibull distribution estimated is different dependent on the number of aircraft. Figure 8 displays that the cases of three and four aircraft searching have

similar results, this is due to the non-optimal search patterns considered for this research. The aircraft are equally split through the region in non-overlapping and optimal search patterns could improve these results. Figure 8 suggest that the Exponential distribution is a reasonable summary distribution for the time until a ship is detected. This Search Pattern model is an operational case without High Altitude Assets for detection or insufficient sensors to detect all tracks in the region, so as to direct the low speed aircraft to classify unknown tracks. In this case, units are required to search independent sectors for tracks and report the new tracks and classification to common data link environment.

Number of Searching Aircraft *Weibull* Distribution PDF $f(x;\lambda,k)=k\lambda\left(x\lambda\right)^{k-1}e^{-(x\lambda)^k}$	**Weibull Parameters** *Weibull* Parameters ($\lambda = Scale$ k=Shape) Characterization ($\mu = Mean$ σ=Standard Deviation)
1	$\lambda = 11.9$ k=1.2 $\mu = 11.2$ σ=9.3
2	$\lambda = 6.4$ k=1.1 $\mu = 6.3$ σ=5.8
3	$\lambda = 4.2$ k=1.1 $\mu = 4.0$ σ=3.6
4	$\lambda = 4.2$ k=1.1 $\mu = 4.0$ σ=3.6
6	$\lambda = 2.6$ k=1.1 $\mu = 2.5$ σ=2.3

Table 9 Weibull Distribution Parameters for Searching Aircraft

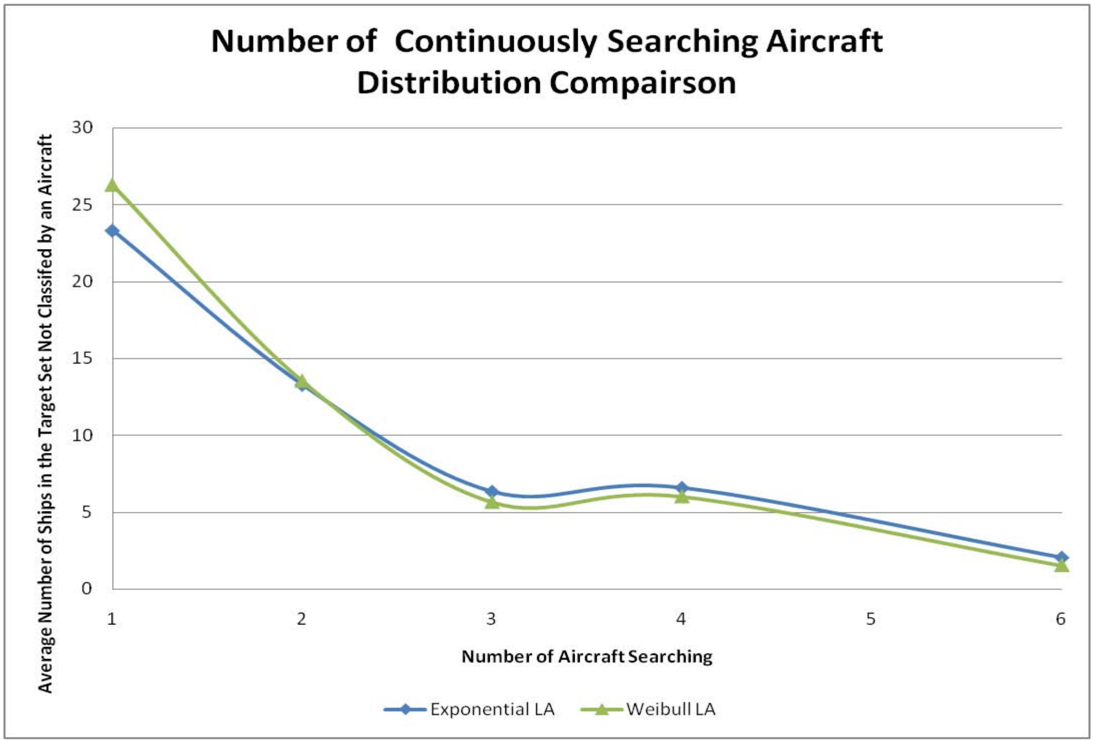

Figure 8 Number of Searching Aircraft Distribution Comparison

Number of Aircraft Searching	Weibull Distribution		Exponential Distribution	
	Mean	Std Error	Mean	Std Error
1	26.32	0.16	23.33	0.15
2	13.54	0.11	13.28	0.12
3	5.66	0.08	6.31	0.08
4	6.02	0.08	6.56	0.08
5	1.53	0.04	2.02	0.05

Table 10 Means and Standard Errors for Figure 6

2. Directed Searching Aircraft

The Directed Searching Aircraft Model assumes there is a High Altitude Aircraft or ship with situational awareness of the Operating Area directing Aircraft over the region to intercept detected but unidentified ships. A JAVA language simulation is

constructed to generate times for the aircraft to intercept an unidentified ship, using the 200 nm x 100 nm area for the search. Using an intercept speed of 100 knots for the aircraft, the time to intercept is determined based on a random ship and aircraft starting position in the area. The ships travel across the region from left to right with a random speed chosen from a Uniform Distribution between 15 and 30 knots. The simulation is replicated 1000 times using one aircraft and one ship and the simulation ends when the ship is within the detection range of the aircraft (five nautical miles). Using these times a Uniform distribution is estimated to summarize the collected data for future analysis. More information on the estimation of the parameters the distribution can be found in Appendix C. The resulting uniform distribution mean compares well to a formula for finding the average distance between two uniform random points in a rectangle (Brahim Gaboune, 1993). A uniform distribution is used to represent a finite aircraft flying time with a fixed maximum flight time, so aircraft do not fly beyond the rectangle to classify ships already out of the zone for intercept surface assets. An exponential distribution is also used to summarize the detection time data. The resulting uniform distribution is used to generate times until the aircraft detection of an unidentified ship in the Imperfect Information-Targeted Boarding model; the resulting exponential distribution is also used. The simulation is replicated 500 iterations over a 96-hour period for the Port of Los Angeles-Long Beach. The scenario assumes that all traffic is in the target set with the number of surface MOTR assets varying. Figure 9 displays the average number of ships not classified by aircraft in the simulation using the estimated uniform and exponential distributions for the aircraft search time and the previous discussed chosen distributions for the Board and Search Time and the Ship Time in Zone.

The average number of ships missed using one aircraft is different for the uniform and exponential aircraft detection times for a single aircraft; the results are very similar for two or more aircraft. Using the exponential distribution to estimate aircraft search time would increase the MOE of Miss Rate for the analytical model for single aircraft scenario. The directed aircraft search method reduces the number of aircraft needed to

detect the ships in the scenario; thus, it is the primary aircraft search method instead of the previous independent searching aircraft method for current and future force structure analysis in the next section.

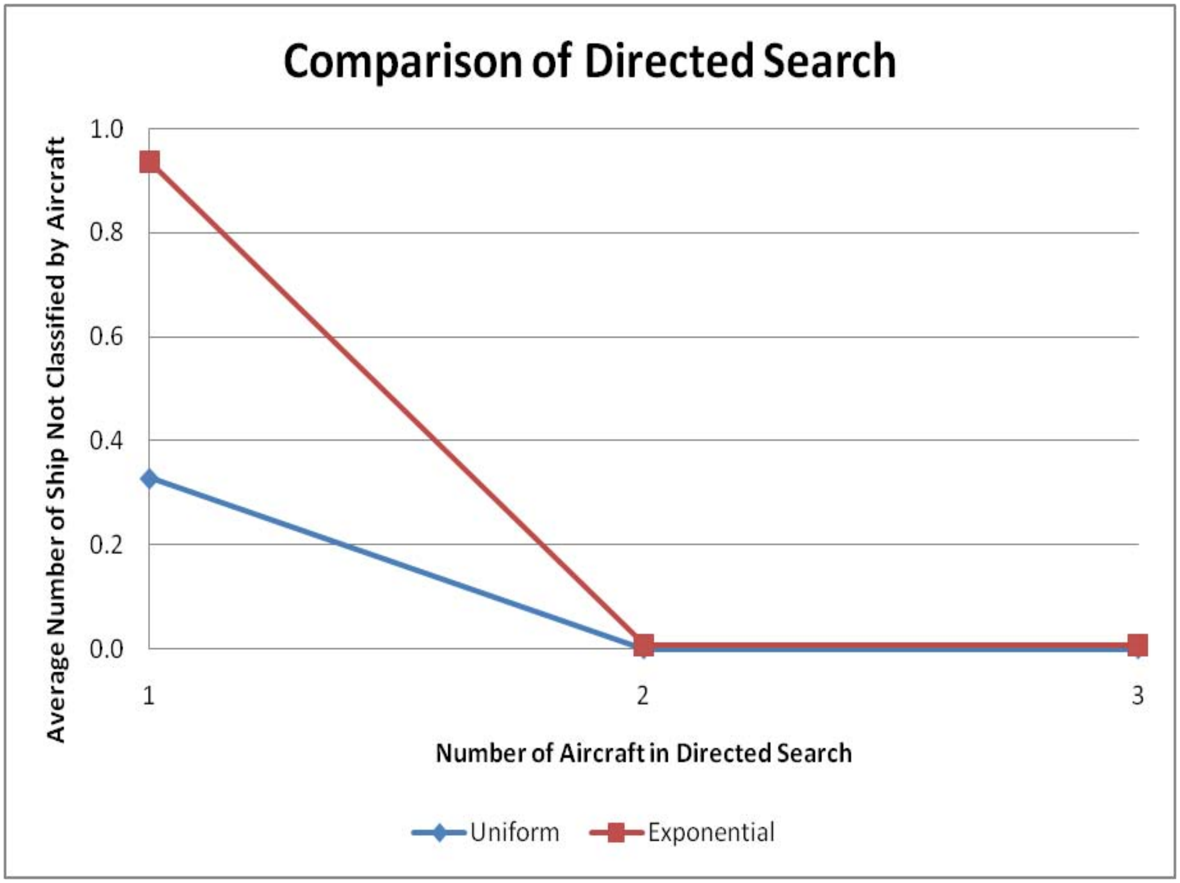

Figure 9 Number of Directed Aircraft Distribution Comparison

Number of Aircraft Searching	Uniform Distribution		Exponential Distribution	
	Mean	Std Error	Mean	Std Error
1	0.328	0.069	0.936	0.137
2	0.000	0.00	0.006	0.004
3	0.000	0.00	0.007	0.004

Table 11 Means and Standard Errors for Figure 9

E. SUMMARY OF DISTRIBUTION ANALYSIS

1. Distribution Sensitivity

In this section, three model inputs are tested for sensitivity to distributional form, the Board and Search Time, the Ship Time in Zone Time, and Aircraft Search Time. The average ship delay is somewhat sensitive to the form of the distribution of the Board and Search Time; however, it is most sensitive to the mean of the distribution. The fraction of ships lost is insensitive to the distribution of the Ship Time in Zone when there is no requirement for classification by aircraft. However, when aircraft are required to classify ships, one aircraft is insufficient to classify all ships passing through the region and as a result, the fraction of ships lost is sensitive to the distributional form of the time ship is in the region. For the Aircraft Search Times in the undirected searching aircraft case, the MOE is insensitive to the Weibull or exponential distributional forms for the time until the aircraft detects a ship. The next chapter compares the MOE results for analytical and simulation models.

2. Final Parameter Values for Analysis

Using the above discussions, the random times and the distributions used to simulate them are displayed in Table 12. These input distributions represent the baseline distributions and are used in the model comparison and simulation studies of all future force structure and force mix scenarios in Chapters IV and V unless otherwise noted.

Random Time	**Distribution Type**	**Parameters**
Board and Search Time	Lognormal $f(x;\mu,\sigma) = \frac{1}{x\sigma\sqrt{2\pi}} e^{-\frac{(\ln(x)-\mu)^2}{2\sigma^2}}$	$\mu = 6$ $\sigma = 2$
Time in Zone	Beta $f(x;\alpha,\beta) = \frac{x^{\alpha-1}(1-x)^{\beta-1}}{B(\alpha,\beta)}$ $X = (h-l)*x+l$	$\alpha = 0.79$ $\beta = 1.31$ $l = 6.70$ $h = 13.65$
Searching Aircraft	Weibull $f(x;\lambda,k) = k\lambda\left(x\lambda\right)^{k-1} e^{-(x\lambda)^k}$	Various see Table 9
Directed Aircraft	Uniform $f(x) = \frac{1}{b-a} \quad for\ a \le x \le b$	$a = 0$ $b = 1.85$

Table 12 Final Distributions and Parameter Values for Analysis

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IV. MODEL COMPARISON

A. COMPARISON DEVELOPMENT

The purpose of this chapter is to explore the simulation and analytical models developed for this scenario. The analytical models provide average results for the more detailed simulation models with less setup and output analysis, but lack the flexibility of different input distributions of the simulations. Each analytical model also provides key bounding results for the simulation scenarios. The development of the analytical models allow for a verification of special cases of the simulation results using the same inputs.

The MOE first considered is the average ship delay. The specific analytical model for the scenario is described in Appendix A. The Arena simulation with only exponential distribution and the Arena simulation with distribution displayed in Table 12 of Chapter III are also considered. For each simulation replication, the average delay for all ships that arrive and leave during the first 96 hours is computed; that is, ships arriving during the 96 hours that have not completed inspection at the end of 96 hours are not counted. The standard errors of the mean are calculated by taking the square root of the sample variance divided by the number of replications. The standard errors associated with mean of the MOE are displayed in tables below their respective figures. This provides a basis of comparison for the models.

B. MINIMAL INFORMATION-100% BOARDING SCENARIO

For the Minimal Information-100% Boarding Scenario, an analytical model based on queuing theory is developed to compare with the Arena simulation developed. Two Arena Simulations are run for comparison using the Minimal Information-100% Boarding Model described in Appendix B. The first uses only exponential distributions for boarding and search times. The second uses the baseline distributions listed in Table 12 in Chapter III. The analytical model is the Multiple-Server Single Stage Queuing Model (M/M/k) described in Appendix A, and the MOE is the long run average ship delay. The analytical model has a limitation in that the server utilization factor must be less than one. For this model, the arrival rate cannot exceed the service rate when all

servers are busy. Since the simulation model can be adjusted to run for a finite time it can provide estimation to the MOE of Average Delay in System for server utilization rates above one. For each simulation replication, the average delay for all ships that arrive and leave during the first 96 hours is computed; that is, ships arriving during the 96 hours that have not completed inspection at the end of 96 hours are not counted. For the model comparison section, the Port of Los Angeles-Long Beach is used with a variable number of boarding teams. Each simulation is run for 500 replications. The same initial random number seed is used to start each simulation. The means and standard errors of each set of replications are listed below the figure in Table 13. The MOE for model comparison is the average delay time of ships into the port.

For the scenario considered the server utilization rate is less than one for the case of five boarding teams and above; and as the utilization rate approaches one the analytical model long run average ship delay approaches infinity. The MOE for the analytical model grows faster than the simulation MOE run for a finite period as displayed in Figure 10. When the server utilization rate decreases, the analytical model reasonably approximates both simulation models. The MOE values for the two simulation models are similar since the MOE is not sensitive to the boarding and search time distribution as discussed in Chapter III. For this scenario, the analytical model is a good approximation for the operation when the server utilization rate is less than one, but is not a good approximation for high density traffic and limited assets causing the server utilization factor to be greater than one.

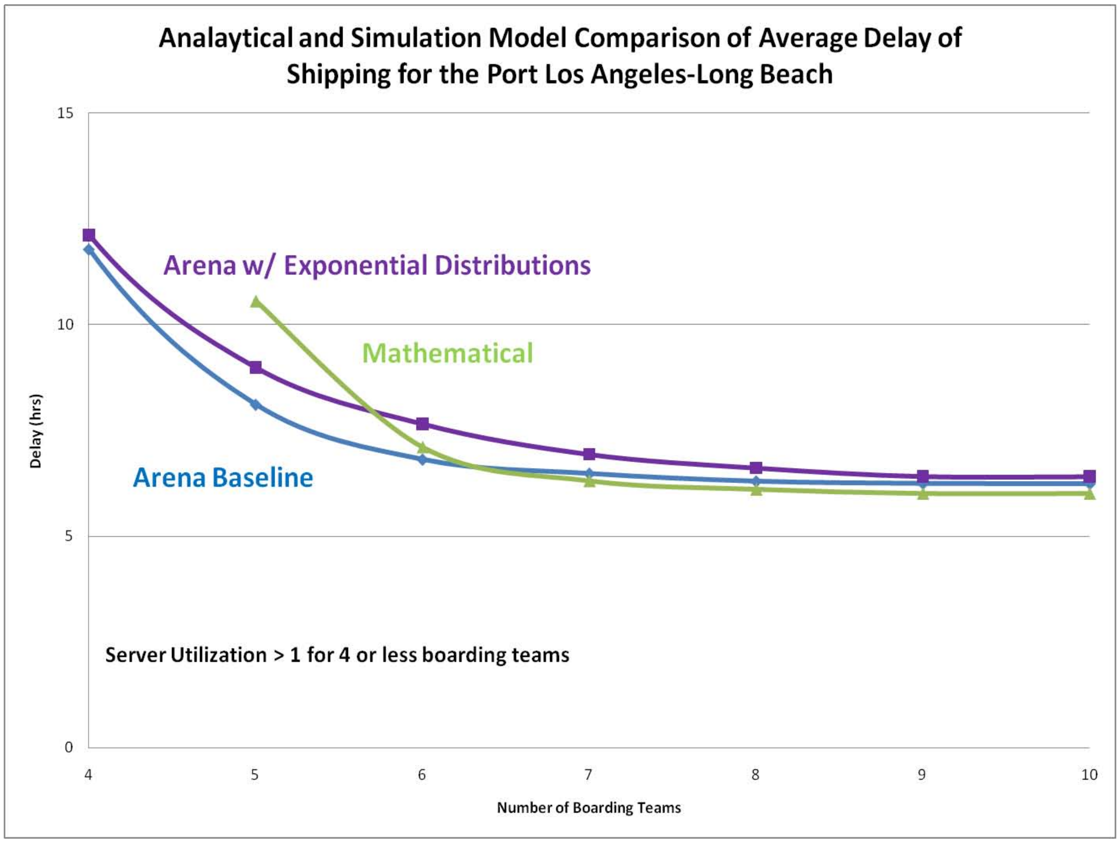

Figure 10 Analytical and Simulation Model Comparison of Average Delay of Shipping for the Port of Los Angeles-Long Beach

Number of Assets	**Analytical**	**Arena w/ Exponential**		**Arena Baseline**	
	Mean	Mean	Std Error	Mean	Std Error
4	-	12.12	0.35	11.78	0.21
5	10.6	8.98	0.35	8.11	0.21
6	7.1	7.65	0.35	6.82	0.21
7	6.3	6.93	0.35	6.48	0.21
8	6.1	6.61	0.35	6.30	0.21
9	6.0	6.41	0.35	6.25	0.21
10	6.0	6.40	0.35	6.24	0.21

Table 13 Means and Standard Errors for Figure 10

C. GOOD INFORMATION-TARGET BOARDING SCENARIO

For the Good Information-Targeted Boarding scenario, the comparison focuses on the comparison of the MOE of Miss Rate using an analytical model and the Arena simulation with different input distributions. There is no requirement for aircraft classification of ships for this scenario. Two Arena Simulations are run for comparison using the Imperfect Information-Targeted Boarding Model described in Appendix B. The first simulation model uses only exponential distributions for the inputs the second uses the baseline distributions listed in Table 12 in Chapter III. The Birth-Death model is a continuous time Markov chain with nonnegative integer state space discussed in detail in Appendix A. The simulation MOE is Miss Rate or fraction of ships in the target set not intercepted by MOTR assets. The MOE for the analytical model is the long run average number of ships per hour lost times 96 hours. The models are compared varying two different factors, varying assets and varying target set percentage. For the model comparison section the Port of Los Angeles-Long Beach is used with a variable number of MOTR assets and variable target set percentage of total traffic, each simulation is run for 500 replications. For each simulation replication, the fraction of ships that arrive during the first 96 hours and are not inspected before they leave the region lost is computed. Ships that arrive during the 96 hours and are still in the region at the end of 96 hours are not counted.

Figure 11 displays the models using the Port of Los Angeles-Long Beach arrival rates with 50% of the traffic in the target set and varying the number of MOTR Assets used in the operation. The analytical model is a reasonable approximation to the simulation results for varying MOTR assets and the two simulation models give similar results. The second figure, Figure 12, considers a case with three MOTR assets. In this figure, the Mathematical model consistently results in higher MOE values, but with similar output shape across the range of inputs as both simulation models. All models give approximately the same value for all data points within maximum difference of 15%, for MOE values less than 50% or when there is more than one MOTR asset

available. The analytical model for the Good Information-Targeted Boarding Case is an excellent approximation to the MOE when there are enough MOTR assets so that the MOE of Miss Rate is below 50%.

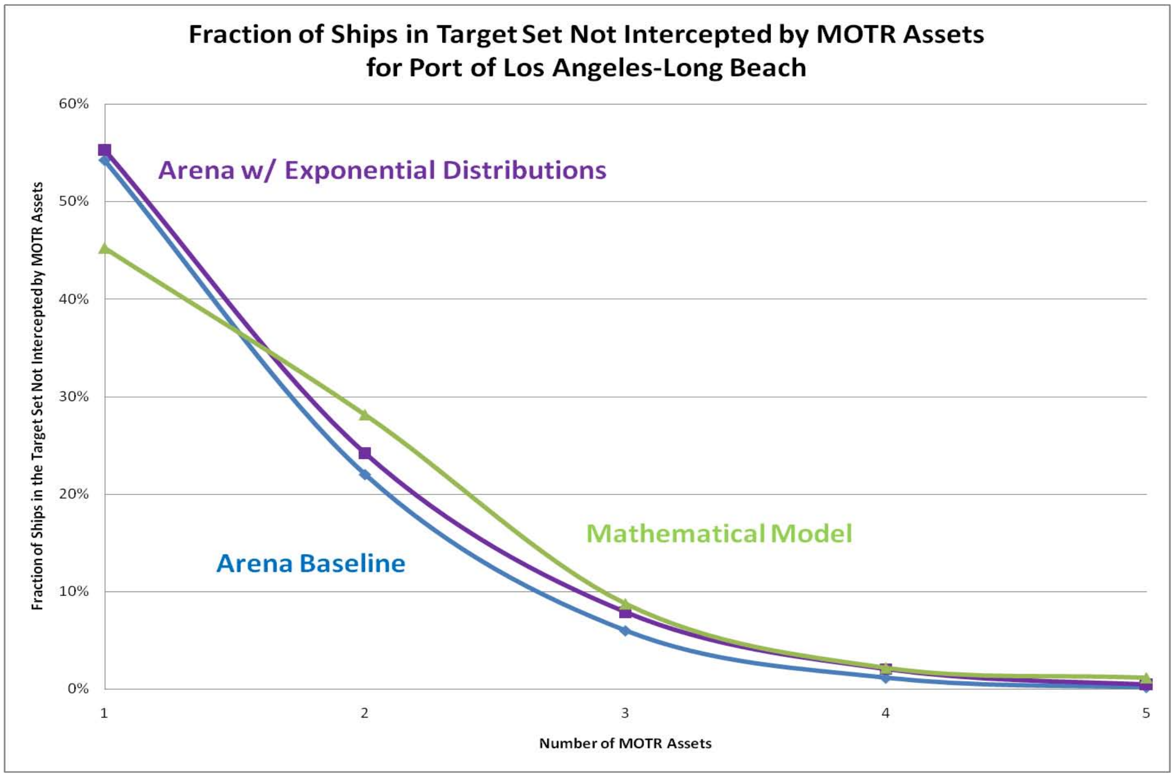

Figure 11 Good Information-Targeted Boarding Model Comparisons of Miss Rate with Varying Assets for the Port of Los Angeles-Long Beach

Number of Assets	**Analytical**	**Arena w/ Exponential**		**Arena Baseline**	
	Mean	Mean	Std Error	Mean	Std Error
1	0.45	0.553	0.005	0.542	0.003
2	0.28	0.242	0.005	0.220	0.004
3	0.09	0.079	0.003	0.060	0.002
4	0.02	0.020	0.002	0.011	0.001
5	0.01	0.004	0.001	0.002	0.000

Table 14 Means and Standard Errors for Figure 11

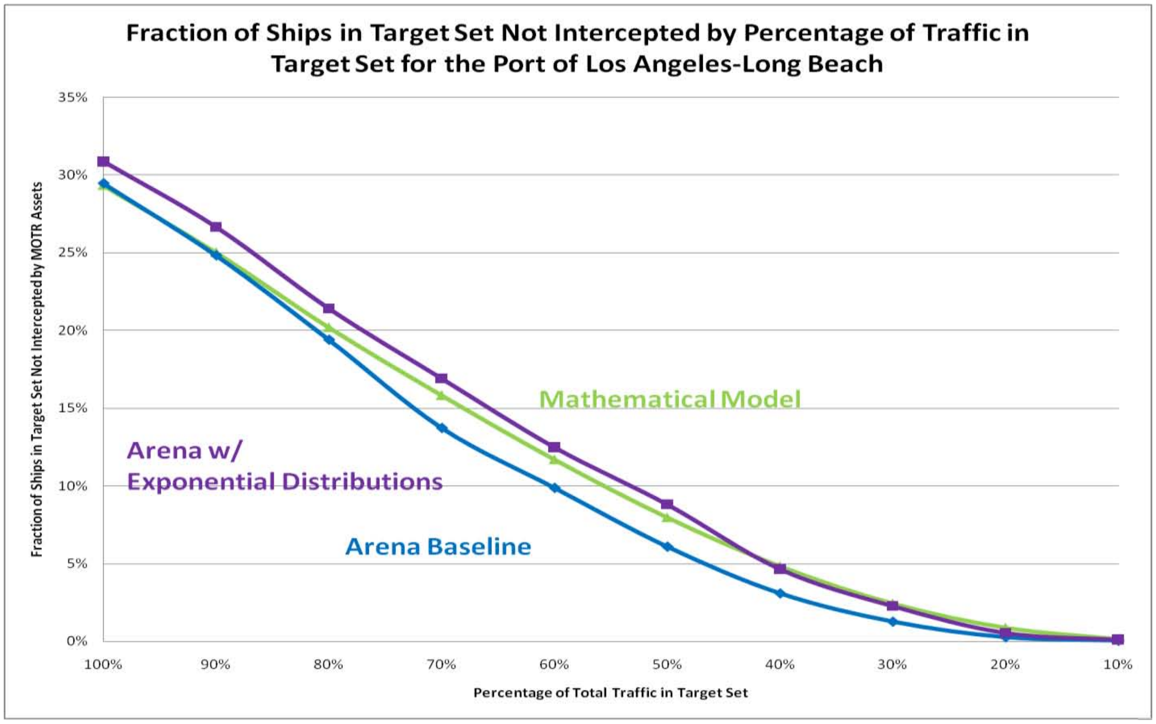

Figure 12 Good Information-Targeted Boarding Model Comparisons of Miss Rate with Varying Target Set Percentage for the Port of LA-Long Beach

Target Set %	**Analytical**	**Arena w/ Exponential**		**Arena Baseline**	
	Mean	Mean	Std Error	Mean	Std Error
10	0.001	0.001	0.000	0.000	0.000
20	0.009	0.005	0.001	0.003	0.001
30	0.024	0.023	0.002	0.013	0.001
40	0.048	0.046	0.003	0.031	0.002
50	0.080	0.088	0.003	0.061	0.002
60	0.117	0.125	0.004	0.099	0.003
70	0.158	0.169	0.004	0.137	0.003
80	0.202	0.214	0.004	0.194	0.003
90	0.250	0.267	0.004	0.248	0.003
100	0.293	0.309	0.004	0.295	0.004

Table 15 Means and Standard Errors for Figure 12

D. IMPERFECT INFORMATION-TARGETED BOARDING SCENARIO

The Imperfect Information-Targeted Boarding scenario is the most complicated scenario developed and several analytical models are developed to approximate the losses. The different cases for this scenario are based on how aircraft classify targets, either by a directed search or undirected search of the area. There are different analytical models to cover both cases. The simulation is modified to use a finite number of aircraft in the directed case. Ships are classified by the aircraft using first come first served discipline. Ship detection for undirected search is simulated as follows: each entering ship is assigned an independent random time until detection having a Weibull or Exponential Distribution.

1. Directed Aircraft

The first set of models represents slow directed aircraft in the simulations and analytical models. The analytical model is a Fluid Model described in detail in Appendix A, which approximates the operation as a system of differential equations with ships passing through the area as the fluid. Two Arena Simulations are run for comparison using the Imperfect Information-Targeted Boarding Model described in Appendix B. The first uses only exponential distributions for the inputs. The second uses the baseline distributions listed in Table 12 in Chapter III. The analytical model has the property of calculating fractional ships traveling through the system without inspection, instead of integer losses in the simulations. The Fluid Model gives lower results for the MOE of Miss Rate compared with the Arena Simulation with exponential distributions for inputs. For the comparison graphs, the Port of Los Angeles-Long Beach arrivals are used, and the first two graphs vary the number of surface MOTR assets in two separate cases for a one aircraft and two aircraft operation. Each case is replicated 500 times and the means and standard errors of the simulation are reported in tables below their respective figures.

Figure 13 displays the Miss Rate for varying number of surface assets with one aircraft and Figure 14 displays Miss Rate with two aircraft operating. The Arena simulation with exponential distributions has the highest MOE values with the fluid model lower due to fractional losses and lastly the Arena simulation using the baseline

distributions. There is a significant difference in the three models for both figures due to losses from a ship passing through the zone without classification from aircraft. The Arena Simulations differ due to the Ship Time in Zone input distribution; the simulation with exponential input distribution has higher MOE values as discussed in Chapter III. Table 18 displays the LA MOE output, or average number of vessels passing through the area not classified by an aircraft. These losses due to aircraft create the disparity in the models when the MOTR assets are in excess, as all models tend to have comparable MOE results when MOTR assets are low. This relative similarity of MOE results with reduced MOTR assets is due to the limited MOTR assets ability to board all classified traffic even though aircraft losses are low.

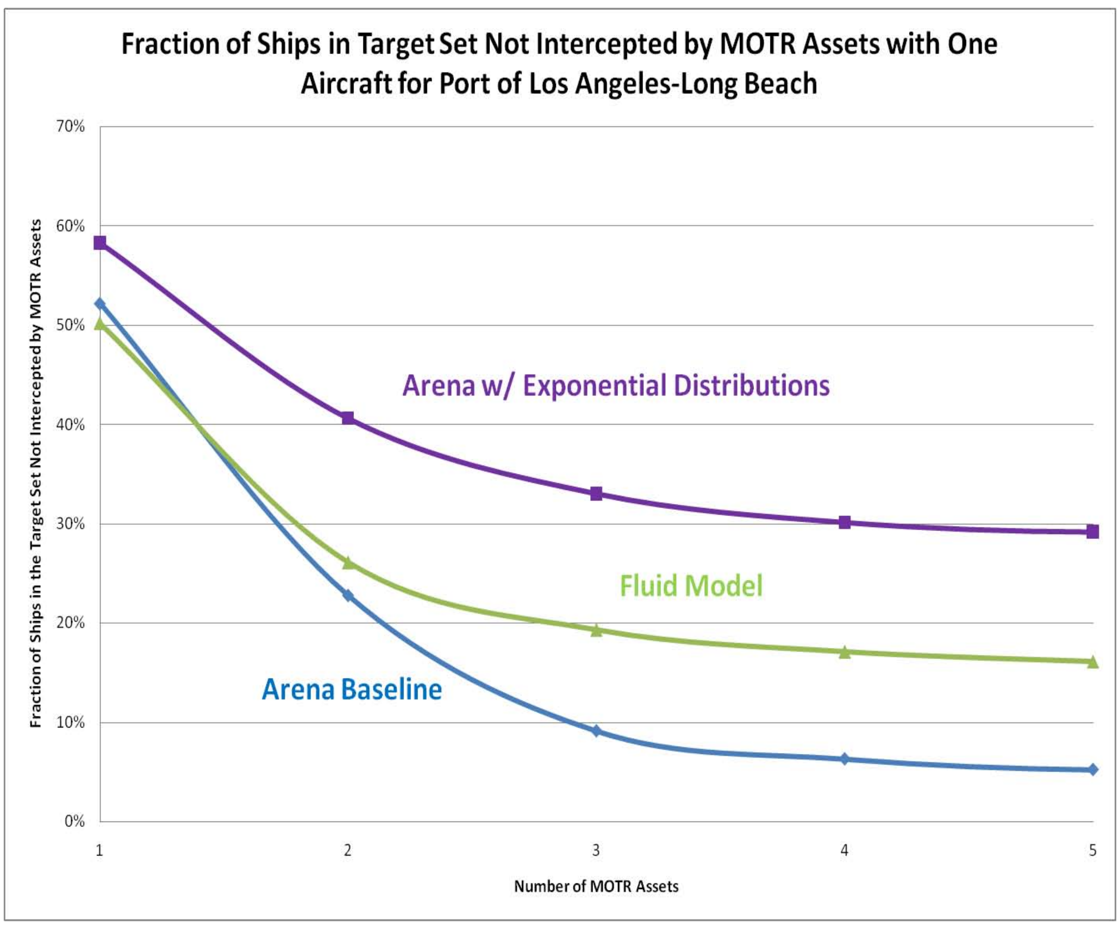

Figure 13 Imperfect Information-Target Boarding Scenario Model comparison with One Directed Aircraft

Number of Assets	Analytical	Arena w/ Exponential		Arena Baseline	
	Mean	Mean	Std Error	Mean	Std Error
1	0.502	0.583	0.004	0.522	0.004
2	0.261	0.406	0.004	0.228	0.004
3	0.193	0.330	0.004	0.091	0.003
4	0.171	0.301	0.004	0.063	0.002
5	0.161	0.291	0.004	0.052	0.002

Table 16 Means and Standard Errors for Figure 13

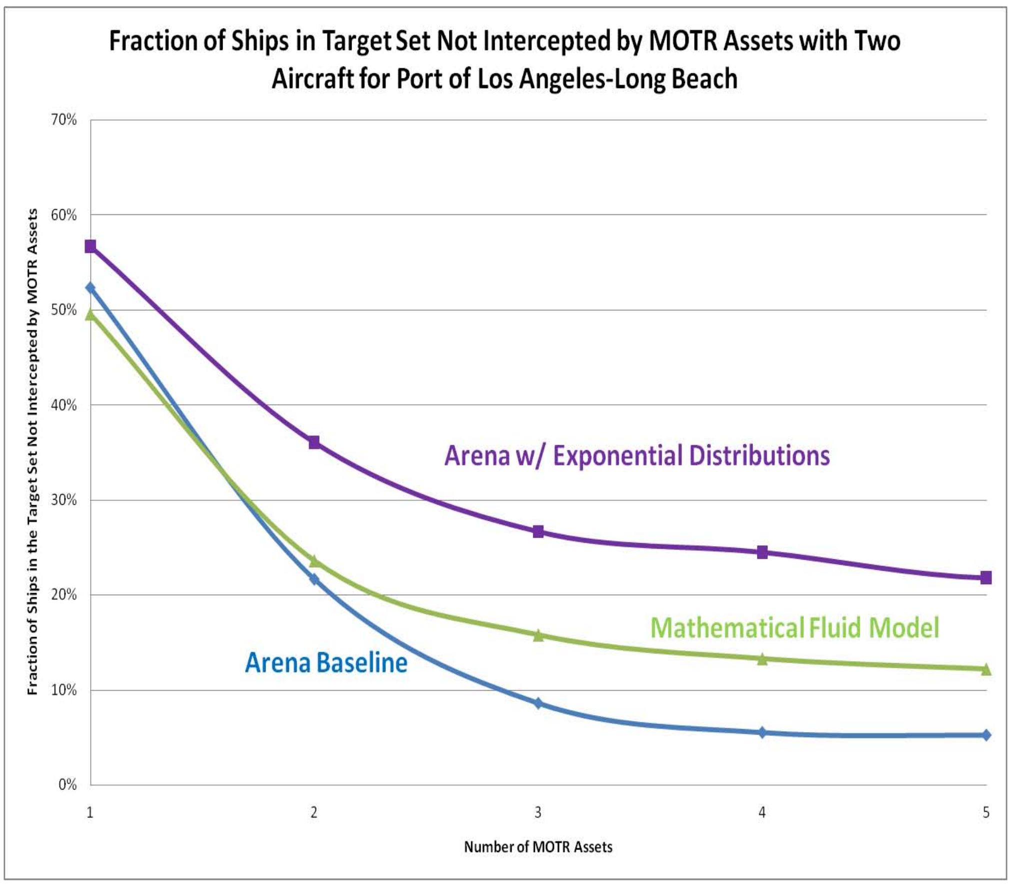

Figure 14 Imperfect Information-Target Boarding Scenario Model comparison with Two Directed Aircraft

Number of Assets	Analytical	Arena w/ Exponential		Arena Baseline	
	Mean	Mean	Std Error	Mean	Std Error
1	0.496	0.567	0.004	0.523	0.004
2	0.236	0.360	0.004	0.216	0.004
3	0.158	0.266	0.003	0.086	0.003
4	0.133	0.245	0.004	0.055	0.002
5	0.122	0.218	0.003	0.052	0.002

Table 17 Means and Standard Errors for Figure 14

Aircraft	Vessels Passing Through the Area Not Classified by an Aircraft		
	Analytical	Arena w/ Exponential	Arena Baseline
1	2.7	5.5	0.1
2	1.4	2.5	0.0

Table 18 Average Number of Ships Passing through the Area without Classification by a Directed Aircraft for Analytical and Simulation Models

2. Undirected Searching Aircraft

In this Imperfect Information-Targeted Boarding scenario case, aircraft are not directed but conduct an undirected search. Three analytical models are considered: a Birth-Death Model; a differential equation Fluid Model; and an M/G/1 Queuing model. These analytical models are described in detail in Appendix A. The birth-death model and the M/G/1 queuing model are used to compute the long run average ship losses per unit time, which are then multiplied by 96 hours to obtain a MOE comparable to the simulation. Two Arena Simulations are run for comparison using the Imperfect Information-Targeted Boarding Model described in Appendix B. The first uses only Exponential Distributions for the inputs and the second uses the slightly modified baseline distributions listed in Table 19. The model for the searching aircraft is one high-

speed Maritime Patrol Aircraft (MPA) aircraft, which is discussed in Chapter V. Each simulation case is replicated 500 times with the means and standard errors reported below the figure. The simulation starts with the same master random number seed for the replications associated with varying input distributions.

Figure 15 displays the MOEs for varying MOTR assets. The results are similar to those obtained with directed aircraft. The Arena with exponential distributions is the results in the largest MOE with the birth death model, Arena Baseline and fluid model yielding similar results with increasing assets. The MOEs for undirected searching aircraft are closer for the analytical and simulation models since the ships in the simulation are not waiting for service by a finite number of aircraft. The analytic Fluid Model's fractional representation of losses or the Birth-Death Model long run average losses are closer to those of the simulation MOE results since all models with Exponential distributions have similar losses due aircraft as displayed in Table 20. The Arena Baseline Model yields the smallest results due to the different ship time in zone distribution. This MOE is sensitive to distribution in the Imperfect Information-Targeted Boarding Scenario because of ships passing through the region without being detected by the aircraft as discussed in Chapter III. Since the Arena Baseline model has a ship in time zone distribution with the smallest variability, this model has minimal losses due to aircraft classification and so reduces its MOE value. The M/G/1 queue is a close approximation of the Arena Simulation with exponential distributions, and its value is within a 95% confidence interval based on the standard error reported below. The analytical models are excellent approximations to the simulation models for this search strategy or if the numbers of aircraft are sufficient to classify all ships in a timely manner.

Model Inputs	Distribution Form for Simulation Model	Distribution Parameters and Means for Models
Number of MOTR Assets	-	Variable
Target Percentage in Target Set	-	50%
Boarding and Search Time (Baseline: Lognormal)	$f(x;\mu,\sigma)=\frac{1}{x\sigma\sqrt{2\pi}}e^{-\frac{(\ln(x)-\mu)^2}{2\sigma^2}}$	$\mu=6,\sigma=2$
Ship Time in Zone (Baseline: Beta Distribution)	$f(x;\alpha,\beta)=\frac{x^{\alpha-1}(1-x)^{\beta-1}}{B(\alpha,\beta)}$ $X=(h-l)*x+l$	$\alpha=2.16,\beta=4.55$ $mean=9.31$
Search Parameter (Baseline: Weibull)	$f(x;\lambda,k)=k\lambda\left(x\lambda\right)^{k-1}e^{-(x\lambda)^k}$	$k=1.70,\ \lambda=1.2$ $mean=1.08$

Table 19 Model Input Parameters for Continuous Searching Aircraft Comparison

Aircraft	Vessels Passing Through the Area Not Classified by an Aircraft				
	Fluid Model	M/G/1 Queue	Birth- Death	Arena w/ Exponential	Arena Baseline
Searching	3.09	3.12	3.13	3.16	0.27

Table 20 Average Number of Ships Passing through the Area without Classification by a Continuous Searching Aircraft for Analytical and Simulation Mode

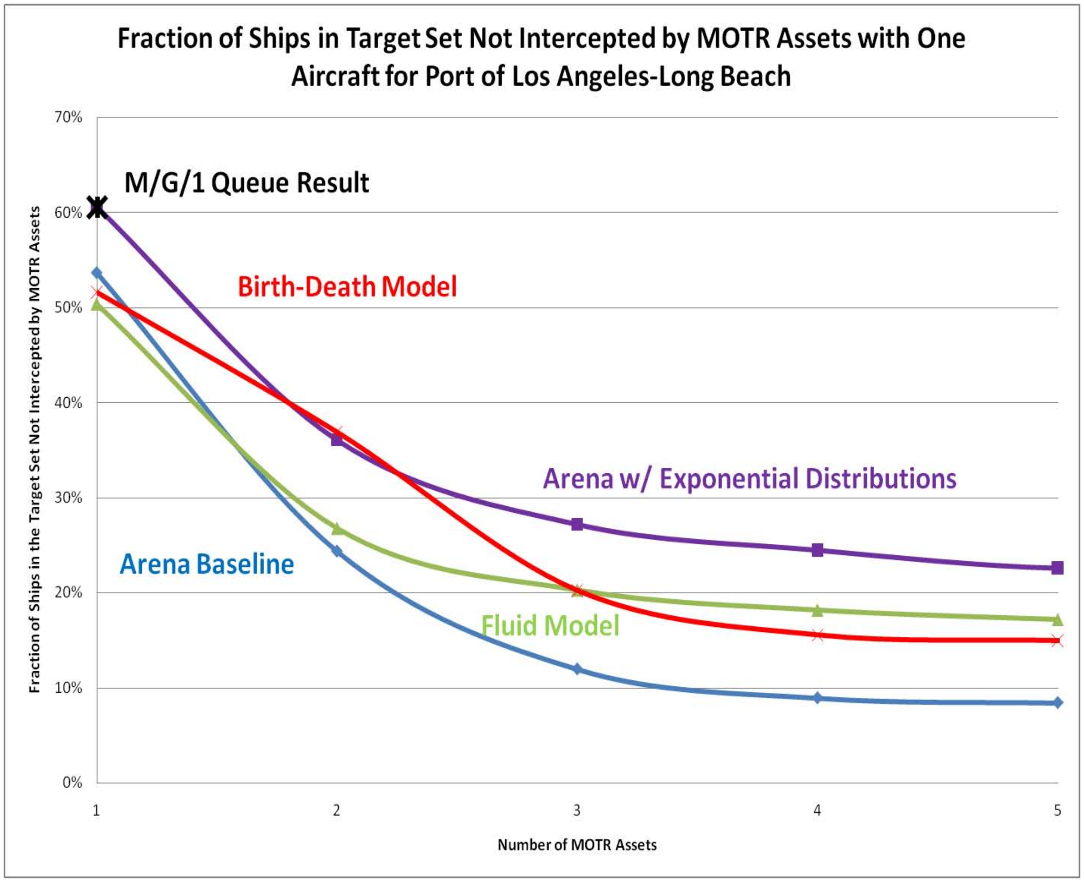

Figure 15 Imperfect Information-Target Boarding Scenario Model comparison with Continuously Searching Aircraft

Number of Assets	**M/G/1 Queue**	**Analytical Fluid**	**Analytical Birth-Death**	**Arena w/ Exponential**		**Arena Baseline**	
	Mean	Mean	Mean	Mean	Std Error	Mean	Std Error
1	0.605	0.504	0.516	0.606	0.004	0.54	0.004
2		0.268	0.369	0.360	0.004	0.24	0.004
3		0.203	0.202	0.272	0.003	0.12	0.003
4		0.182	0.155	0.244	0.003	0.09	0.002
5		0.172	0.149	0.225	0.003	0.08	0.002

Table 21 Means and Standard Deviation for Figure 15

E. SUMMARY OF MODEL COMPARISON

In this chapter, the analytical and simulation models for each of the three scenarios were compared for the respective MOEs. For the Minimal Information-100% Boarding scenario, the analytical model is a good approximation for the MOE in cases where the server utilization rate is less than one or when there is adequate MOTR assets to meet the shipping demands of the port. In the Good Information-Targeted Boarding scenario, the analytical model is a good approximation of the Miss Rate MOE. In this scenario, both simulations and the birth death model provide similar results and the same shape for the MOE in the varying assets and varying target set percentage cases. For the aircraft models, the analytical models tended to have higher MOE results for Miss Rate due to losses by aircraft. In the directed aircraft case, the Fluid Model is a reasonable approximation when forces are limited, but the Fluid model provides the average value between the exponential and baseline simulation models. For the undirected searching aircraft case, the fluid model has the same average value between the exponential and baseline simulation models; while the M/G/1 queue and Birth-Death model are reasonable approximations to the simulation model with exponentially distributed random time variables. The analytical models in all the scenarios are reasonable values for general planning for respective MOEs concerning the west coast ports, especially when more detailed information for the simulations is not known or available.

V. RESULTS AND ANALYSIS

A. FORCE STRUCTURE AND PLANNING

In this section, the simulations described in previous sections are used to evaluate the MOTR organization number and mix of platforms, tactics, and sensors needed to protect the U.S. West Coast Ports today and into the future. The models developed allow flexibility for the user to vary the inputs and to select the desired risk level and force structure for the situation or threat. The targeted scenarios below are used to demonstrate the models' ability to evaluate current force structure; aircraft search strategies, and future force structure for the growing ports.

A key factor in the analysis is the fraction of the total traffic in the target set. This can be the percentage of traffic from a specific port (e.g., Shanghai), a specific type of ships (e.g., Container Ship), or specific flag or ownership group. By using collected intelligence to reduce the traffic of interest to a target set, a reduced number of air and sea assets can profile traffic of interest allowing the ports to stay open and mitigating the economic consequences of closing or delaying port traffic.

In the simulations with aircraft conducting initial classification, there is 5% chance for misclassification for all scenarios. The aircraft has a conditional probability to identify the ship correctly as Red or White given the ship is Red or White, to account for operator or judgment error. This 5% error could also represent misclassification by previous intelligence, which did not put a target of interest in the target set prior to operation; intelligence may also put a ship not of interest into the target set. Due to this misclassification percentage, the assets never achieve a 0% Miss Rate. Rather, when there is a force excess, the resultant Miss Rate is close to 5%. These conditional classification probabilities are adjustable and are used to represent the "fog of war" for this type of operation.

1. Current USCG Force Structure

The first part of the analysis focuses on the current USCG force structure assigned to the West Coast Ports using the WHEC, WMEC, and NSC class cutters. These USCG

assets have the endurance and organic air assets to conduct this mission of maritime intercept outside territorial waters for prolonged periods of time. The current force structure and arrival rates for the ports are listed again below in Table 22. The Minimal Information-100% Boarding Scenario and the Imperfect Information-Targeted Boarding Scenario is used as the models for the current force structure analysis.

Port Description	Arrival Rates (Ships/ Day)	USCG Cutters at the Port
Seattle-Tacoma	6.5	3
Columbia River Ports	7.0	2
San Francisco Bay Ports	10.8	3
Los Angeles-Long Beach	15.1	4

Table 22 Current Arrival Rates and USCG Assets at West Coast Ports

a. Current Force Structure for Total Inspection

For this case, minimal information is known on the target and all arriving traffic is in the target set. This is a "worst-case" for the port since the risk is high and prior intelligence does not allow the target set to be reduced to limit the incoming threat. This scenario also forces the port traffic to slow down while VBSS operations continue offshore. This delay of traffic into the ports could have detrimental effects on the economy of the United States. For example the Longshoreman strike along the West Coast in 2002 lasted for 10 days and cost the U.S. economy approximately one to two billion dollars a day (Assoicated Press, 2007). For this case, two boarding parties per MOTR asset are used since the traffic is boarded in a holding area and the MOTR assets can maintain contact with boarding teams due to relatively short distances between target ships. A restriction of a 14-hour workday is enforced to allow a rest and recovery period for the boarding parties. The critical MOE is the Average Delay time to the port. This MOE is a measure of lost productivity since all traffic is held at least several hours while boarding teams search incoming ships. The simulation uses the arrival rates in Table 22

and the distribution of the board and search time is modeled with the lognormal distribution having a mean six hours and standard deviation two hours. It is assumed that the ships are boarded in the order of their arrival. For each replication, the delay of all ships that arrive and leave during the first 96 hours is computed and divided by the number of ships that arrive and leave in 96 hours. Ships that have not completed inspection at the end of 96 hours are not counted. The number of simulation replications is 500 and the simulation starts each ports replication set on the same random number seed value. Figure 16 below displays the Average Delay time as a function of the expected VBSS time for the boarding teams. The standard errors of the mean calculated by taking the square root of the sample variance divided by the number of replications, associated with the mean boarding time are displayed in tables below their respective figures. Figure 16 demonstrates the advantage of new technology to reduce VBSS times and thereby reduce overall ship delays. The next figure, Figure 17, displays the effect of Operational Availability on the Average Delay Time, where Operation Availability is the percentage of boarding parties able to participate in the mission from the assigned forces in Table 22. The number of boarding parties participating in each operation is the Operational Availability multiplied by the number boarding teams available in the baseline case, rounded down if not an integer value.

This figure shows the effect of losses to the force or to boarding teams within the force on the MOE. These losses of assets could be due to maintenance availability, current mission tasking, and other planning requirements. The figure displays increased risk due to loss of assets and the need for additional supporting MOTR forces to the current USCG force structure. For the case of the Columbia River Ports between 40% and 60% operational availability, the slight decrease is due to simulation variability. The MOE values for the Operational Availability percentages are not statistically different using a 95% confidence interval and the standard errors reported. Both figures display how delay time can grow with loss of assets without additional forces in low Operation Availability cases, especially in the case of the busiest port of Los Angeles-Long Beach or the case with relatively few assets to support the operation in the Columbia River

Ports. These figures display a need to mitigate risk with advanced search technology, additional forces, and different tactics to limit port delays and the loss of productivity for the ports.

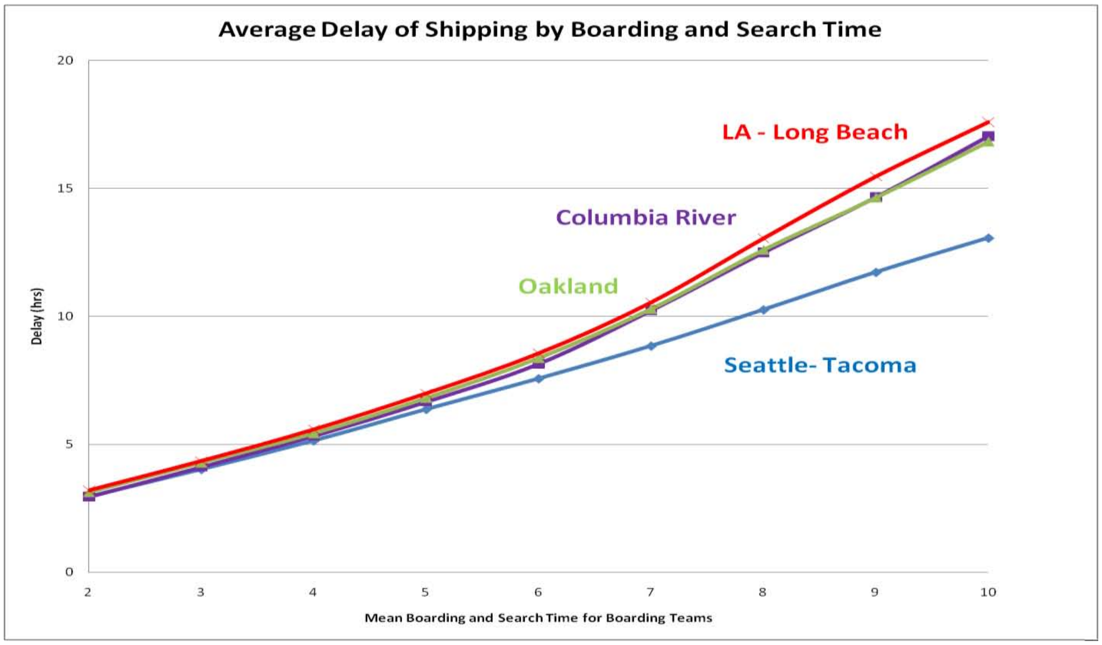

Figure 16 Current Force Structure Average Delay of Shipping for No Information-100% Board Scenario based on Mean Search Time of MOTR Assets

Average VBSS Time	**Seattle-Tacoma**		**Columbia River**		**San Fran Bay**		**LA-LB**	
	Mean	Std Error	Mean	Std Error	Mean	Std Error	Mean	Std Error
2	2.96	0.16	2.94	0.22	3.13	0.22	3.20	0.23
3	4.03	0.16	4.11	0.22	4.28	0.22	4.35	0.23
4	5.15	0.16	5.32	0.22	5.43	0.22	5.58	0.23
5	6.37	0.16	6.66	0.22	6.81	0.22	6.99	0.23
6	7.57	0.16	8.14	0.22	8.37	0.22	8.55	0.23
7	8.85	0.16	10.22	0.22	10.29	0.22	10.54	0.23
8	10.26	0.16	12.49	0.22	12.60	0.22	13.04	0.23
9	11.72	0.16	14.65	0.22	14.64	0.22	15.46	0.23

Average VBSS Time	Seattle-Tacoma		Columbia River		San Fran Bay		LA-LB	
	Mean	Std Error	Mean	Std Error	Mean	Std Error	Mean	Std Error
10	13.06	0.16	17.03	0.22	16.83	0.22	17.58	0.23

Table 23 Means and Standard Errors for Figure 16

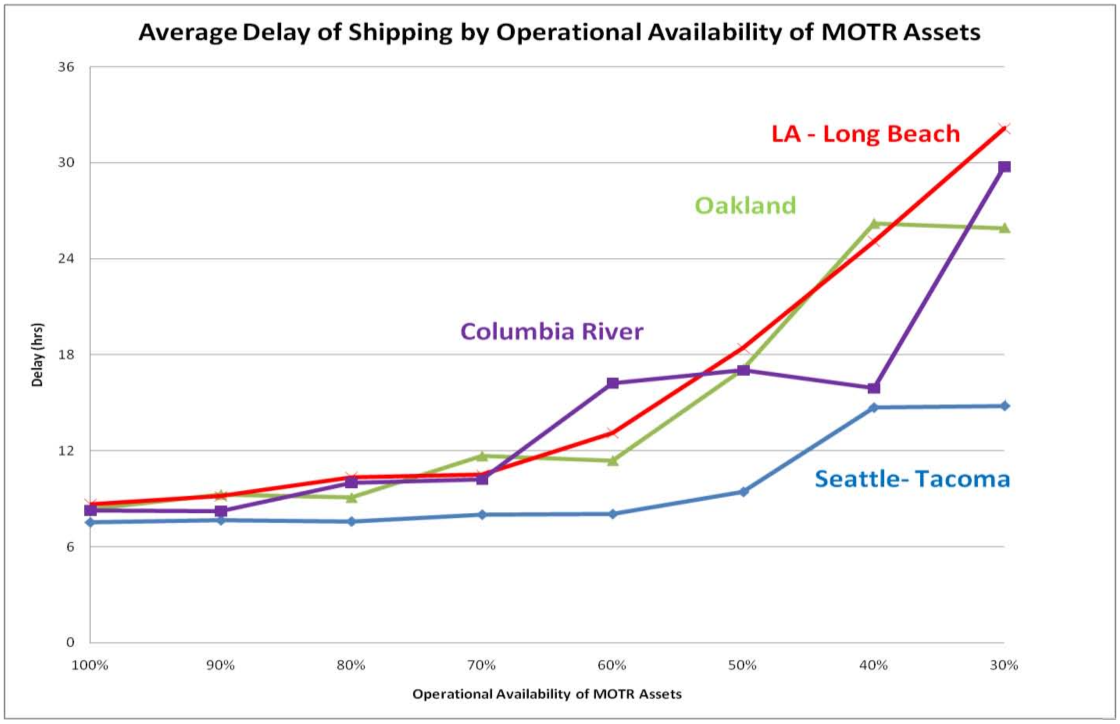

Figure 17 Current Force Structure Average Delay of Shipping for No Information-100% Board Scenario based on Operational Availability of MOTR Assets

Op Avail %	Seattle-Tacoma		Columbia River		San Fran Bay		LA-LB	
	Mean	Std Error	Mean	Std Error	Mean	Std Error	Mean	Std Error
100	7.52	0.31	8.28	0.42	8.33	0.46	8.64	0.44
90	7.65	0.31	8.23	0.42	9.25	0.46	9.14	0.44
80	7.58	0.31	10.01	0.42	9.06	0.46	10.34	0.44

Op Avail %	Seattle-Tacoma		Columbia River		San Fran Bay		LA-LB	
	Mean	Std Error	Mean	Std Error	Mean	Std Error	Mean	Std Error
70	8.00	0.31	10.20	0.42	11.65	0.46	10.49	0.44
60	8.04	0.31	16.24	0.42	11.37	0.46	13.11	0.44
50	9.42	0.31	17.05	0.42	17.09	0.46	18.42	0.44
40	14.68	0.31	15.92	0.42	26.19	0.46	25.09	0.44
30	14.79	0.31	29.78	0.42	25.93	0.46	32.16	0.44
20	28.32	0.31	30.10	0.42	36.64	0.46	32.77	0.44

Table 24 Means and Standard Errors for Figure 17

b. Target Set Limiting for Open Port Operations

This scenario is the economic friendly scenario using the current force structure to stop a vessel with dangerous cargo before it reaches U.S. Territorial Waters and allowing the port to stay open with minimal delays to friendly traffic. This case is best approximated by the Imperfect Information-Targeted Boarding scenario. For the figures below, two directed aircraft are used to increase the likelihood of intercepting targets and a variable target set is specified from the total traffic into the port. The target set is comprised of ships from a percentage of total port traffic that are deemed suspicious based on previous intelligence information. All other inputs including distributions for Ship Time in Zone, Boarding and Search Time, and Aircraft Search Time are discussed in Chapter III and summarized in Table 12. Each Target Set percentage scenario is replicated 500 times. The means and standard errors for each case are displayed in tables below each figure. The simulation starts each port's set of replication on the same master random number seed.

For Figure 18 below, with the exception of Columbia River Ports, the MOTR assets available for the mission are the current USCG forces assigned to each port minus one asset, to represent unavailability due to maintenance or other operational commitment. If the Columbia River Ports are limited to one MOTR asset rather than the

two it currently assigned, the target set must be reduced below 10% of the total traffic so the risk of missing a red ship is less than 10%. The graph below displays the Columbia River Ports with two assets operating. Figure 18 displays the effect on the MOE Miss Rate, the fraction of traffic in the target set not boarded by MOTR assets, due to limiting the percentage of total traffic in the target set. Using a criterion risk of a 10% Miss Rate, the target set needs to be reduced below 40% of the total traffic for the current assigned force levels to be sufficient to protect the ports at this risk level. The simulation assumes that each entering ship to the port is a member of the target set independently from ship to ship. If the assignment of ships to the target set is dependent then the results may be different (e.g., if one ship is assigned the target set then the next ship is more likely to be assigned to the target set). This type of analysis supports the desirability of pre-mission intelligence prior to the operation to limit the boarding targets for the assets currently available at each port.

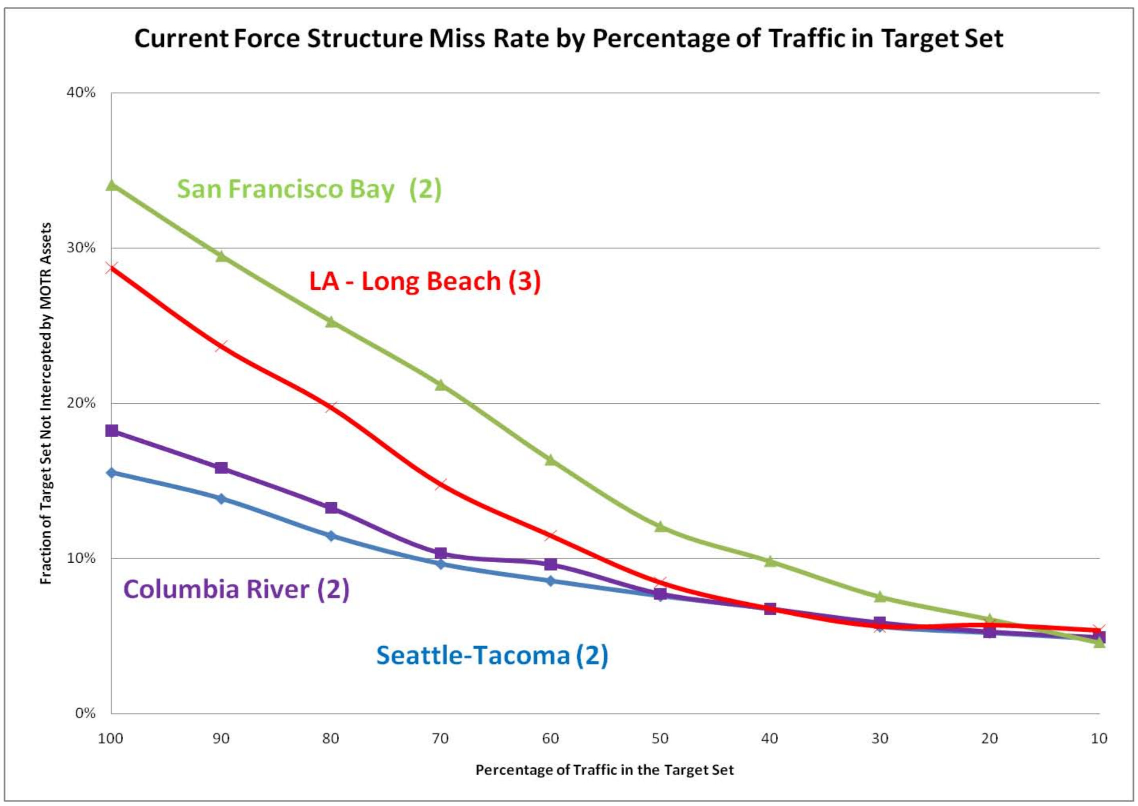

Figure 18 Current Force Structure results for Miss Rate by Percentage of Traffic in the Target Set (MOTR Assets for Each Port Listed in (#) by Port Name)

Target Set %	Seattle-Tacoma		Columbia River		San Fran Bay		LA-LB	
	Mean	Std Error	Mean	Std Error	Mean	Std Error	Mean	Std Error
10	0.048	0.007	0.049	0.007	0.046	0.005	0.053	0.004
20	0.052	0.007	0.052	0.007	0.061	0.005	0.057	0.004
30	0.056	0.007	0.058	0.007	0.075	0.005	0.056	0.004
40	0.067	0.007	0.067	0.007	0.098	0.005	0.067	0.004
50	0.076	0.007	0.077	0.007	0.121	0.005	0.084	0.004
60	0.085	0.007	0.096	0.007	0.164	0.005	0.115	0.004
70	0.096	0.007	0.103	0.007	0.212	0.005	0.148	0.004
80	0.115	0.007	0.132	0.007	0.253	0.005	0.197	0.004
90	0.138	0.007	0.158	0.007	0.295	0.005	0.237	0.004
100	0.155	0.007	0.182	0.007	0.341	0.005	0.287	0.004

Table 25 Means and Standard Errors for Figure 18

2. Aircraft Force Structure Flexibility

In this section, the numbers of air assets and surface assets to defend the ports is studied. The Imperfect Information-Targeted Boarding scenario is used to create the graphs below on aircraft force structure. From the discussion in Chapter III on directed aircraft, for the parameter values considered one aircraft results in some ships lost due to non-classification by an aircraft while two aircraft eliminated this type of loss in all ports. For the scenario considered in this section the general aircraft type is modeled by using an average speed of 100 knots to represent small UAVs and Helicopters organic to the cutters. The actual number of aircraft to keep one or two aircraft airborne for the duration of the operation would be a greater number based on a variety of factors including air platform endurance, reliability, and the surface assets ability to support specific types of aircraft. The simulation starts each set of replication for a port on the same master random number seed. The other parameters for the graphs are discussed in Table 12 in Chapter III, with the target set equal to 50% of the incoming traffic. The first graph,

Figure 19 displays the effect on Miss Rate using one aircraft and varying the number of MOTR surface assets to determine the risk vs. reward projection for each port. The second, Figure 20, displays the same MOE and varying then the number MOTR surface assets with two aircraft patrolling at all times.

Both Figures 19 and 20 are very similar in shape, since adding an aircraft to the operation does not influence the MOE much. The target set losses due to aircraft are minor compared to the losses due to lack of surface assets. Based on the projections in Chapter III, additional aircraft do not affect the critical MOE, since losses due to a lack of aircraft classification are negligible. For the parameters of this scenario, aircraft are not critical to the MOE of Miss Rate and other factors must be adjusted; for example, percentage of traffic in target set may be decreased or the number of surface assets may be increased to improve MOE results for a specific port.

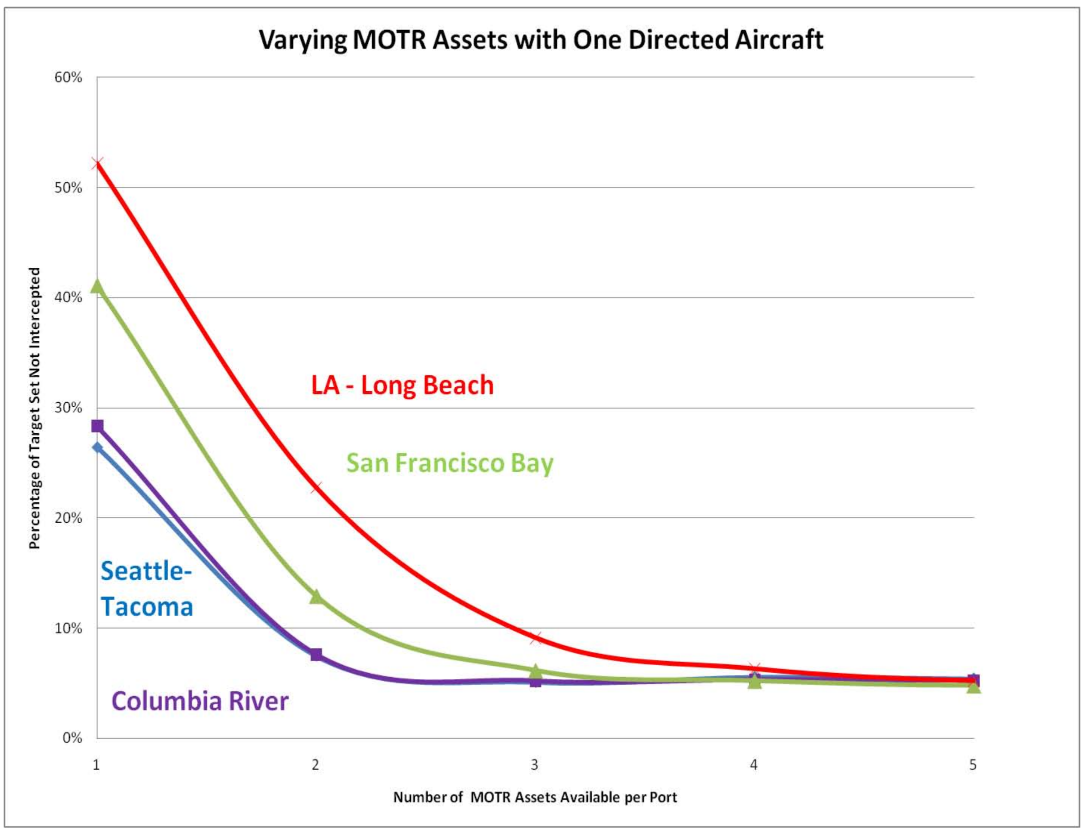

Figure 19 Varying Force Mix with One Patrolling Aircraft

Number of Assets	**Seattle-Tacoma**		**Columbia River**		**San Fran Bay**		**LA-LB**	
	Mean	Std Error	Mean	Std Error	Mean	Std Error	Mean	Std Error
1	0.264	0.006	0.284	0.006	0.411	0.005	0.522	0.004
2	0.075	0.006	0.076	0.006	0.129	0.005	0.228	0.004
3	0.051	0.006	0.052	0.006	0.062	0.005	0.091	0.004
4	0.056	0.006	0.053	0.006	0.052	0.005	0.063	0.004
5	0.054	0.006	0.053	0.006	0.048	0.005	0.052	0.004

Table 26 Means and Standard Errors for Figure 18

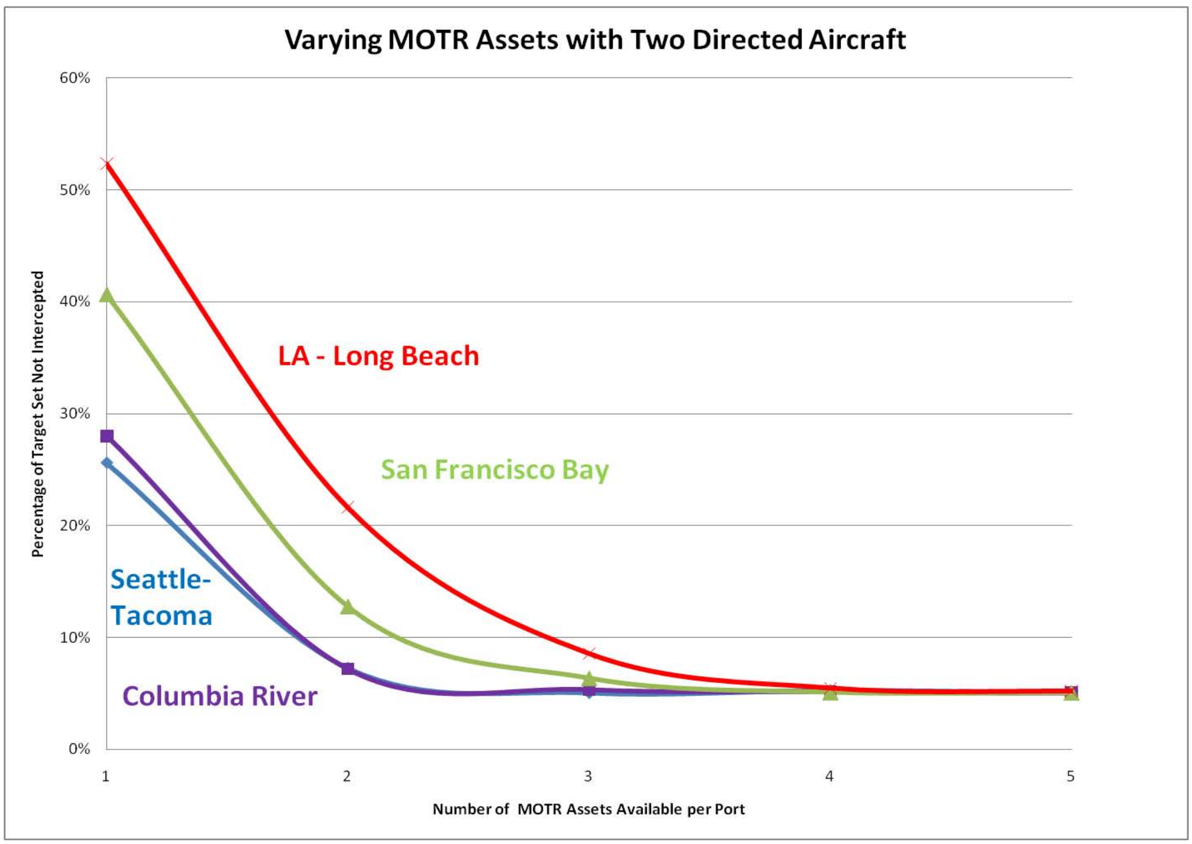

Figure 20 Varying Force Mix with Two Patrolling Aircraft

Number of Assets	Seattle-Tacoma		Columbia River		San Fran Bay		LA-LB	
	Mean	Std Error	Mean	Std Error	Mean	Std Error	Mean	Std Error
1	0.256	0.005	0.280	0.005	0.407	0.005	0.523	0.004
2	0.073	0.005	0.072	0.005	0.128	0.005	0.216	0.004
3	0.051	0.005	0.054	0.005	0.064	0.005	0.086	0.004
4	0.053	0.005	0.052	0.005	0.051	0.005	0.055	0.004
5	0.051	0.005	0.051	0.005	0.051	0.005	0.052	0.004

Table 27 Means and Standard Errors for Figure 20

3. Effect of Maritime Patrol Aircraft on Non-Directed Search

In a previous chapter, discussing specification of the distributions of times represented in the simulation, non-directed aircraft are modeled conducting ladder searches of the operating area at slow speeds to represent small UAVs and Helicopters doing undirected searches. This section explores the use of fast moving Maritime Patrol Aircraft, for example, the Navy's P-8 Poseidon or the Coast Guard's C-130 Hercules. Using the same Java simulation and Censored Data analysis method detailed in Appendix C, the parameters of a Weibull distribution are estimated for the faster moving Maritime Patrol Aircraft (MPA) aircraft. For the simulation, the aircraft are given a speed of 400kts and visual only detection/classification ranges of 5nm, which is the same as the slower aircraft in previous sections. Figure 21 displays the effect of the faster moving aircraft on the MOE of Average Number of Targets Not Classified by an Aircraft (LA). Two high speed Maritime Patrol Aircraft conducting an undirected search have a similar effect on the MOE as that of a single low speed aircraft conducting a directed search; the high speed MPA and low speed directed aircraft use a visual only detection with a five nautical mile maximum range.

Next, the same simulation is exercised but with the MPA's maximum sensor range increased to 12 nm to represent an enhanced camera system. The MOE displayed in Figure 22 suggest that in this case a single high speed undirected searching aircraft

results in similar MOE values as low speed aircraft with a directing source. For this case, increasing the sensor range for an MPA aircraft reduces the number of assets needed for the mission by one half, which emphasizes the need for long range all weather sensors that can classify targets at beyond human visual range. The MPA case is an important case when low speed sea based assets could not fly due to environmental factors or their unavailability for maintenance. The use of MPA aircraft may have additional advantages including increased Situational Awareness from the ability of MPA to maintain a communications and data link coverage for the Operational Area. MPA are not an organic asset to surface assets. However, most MPA aircraft have longer on station times, which could be critical gap filler when organic air assets are unavailable or tasked with other missions.

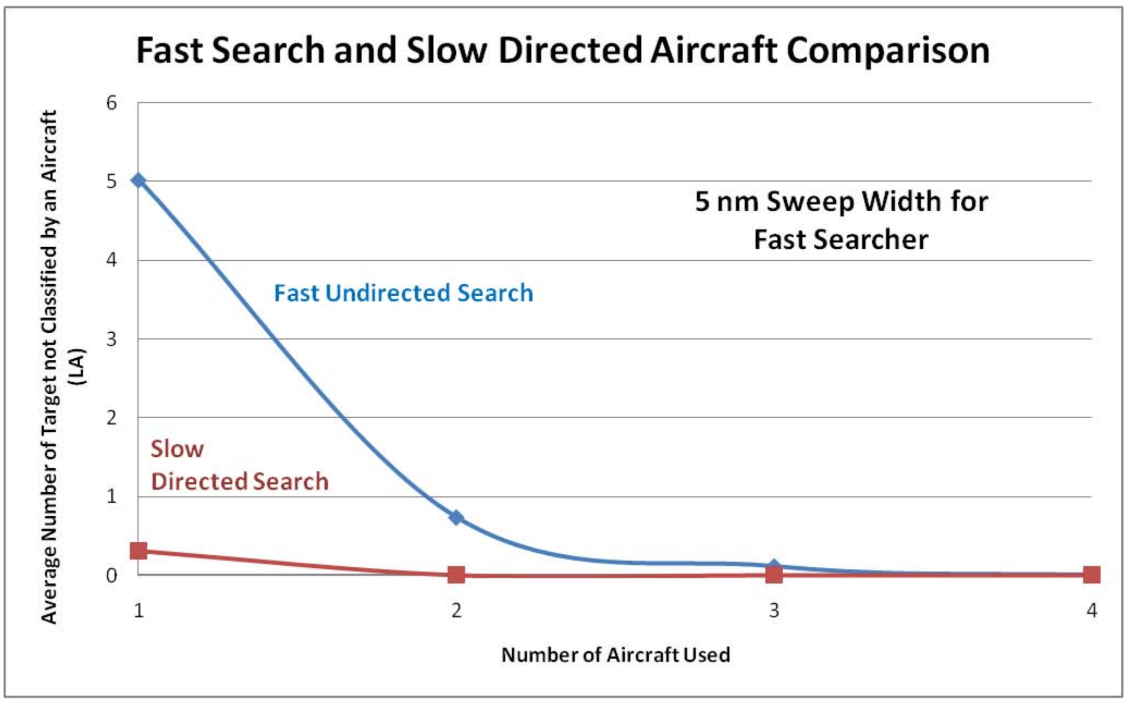

Figure 21 Fast Undirected Search and Slow Directed Search Missed Targets Comparison with 5 nm Visual Sweep Width

Number of Aircraft	Slow Directed		Fast Undirected	
	Mean	Std Error	Mean	Std Error
1	0.306	.069	5.071	0.073
2	0	0	0.709	0.028
3	0	0	0.112	0.011
4	0	0	0	0.000

Table 28 Means and Standard Errors for Figure 21

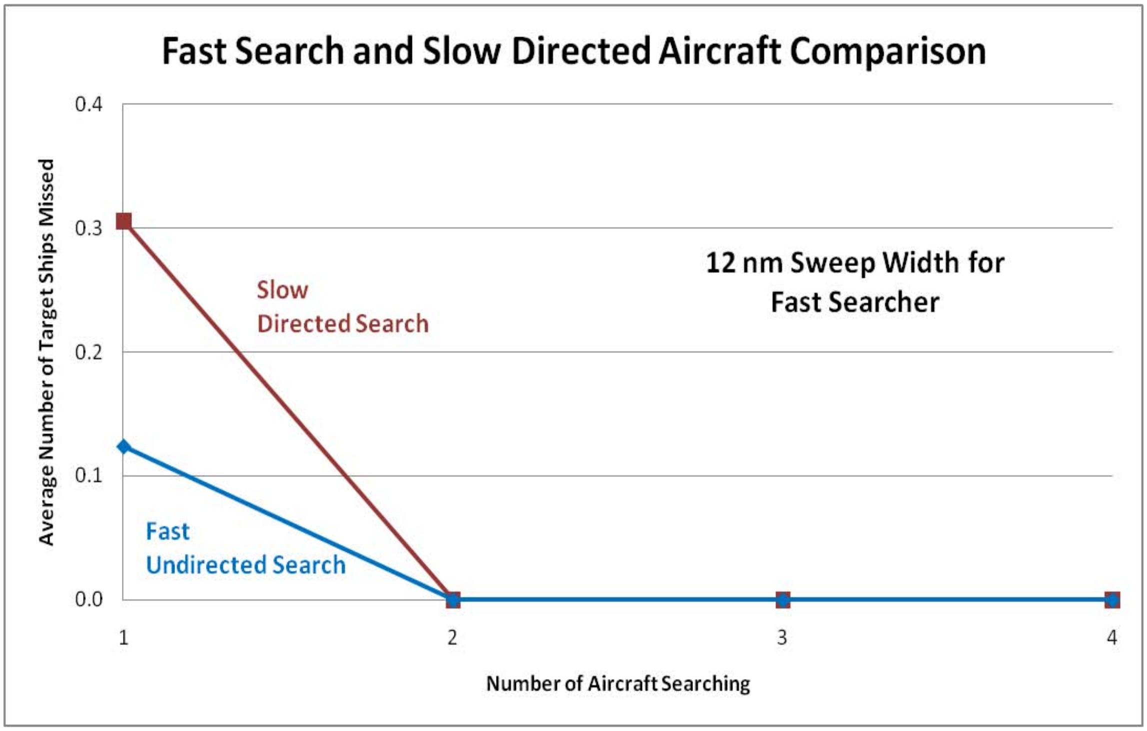

Figure 22 Fast Undirected Search and Slow Directed Search Missed Targets Comparison with 12 nm Visual Sweep Width

Number of Aircraft	Slow Directed		Fast Undirected	
	Mean	Std Error	Mean	Std Error
1	0.306	.069	0.124	0.016
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

Table 29 Means and Standard Errors for Figure 22

B. ADDITIONAL SCENARIOS

The flexibility of the models developed for the present day force structure analysis allows two additional scenarios to be evaluated. The first scenario is to project future arrival rates into the West Coast Ports and to assess the force structure in 2015 and 2020. Second, the models are used to evaluate the risk of vessels less than 300 tons against U.S. ports based on the number of target ships in the operating area. Both scenarios represent current areas of interest for the Department of Homeland Security and the Department of Defense Homeland Defense Offices.

1. Projected Force Structure

To predict the increased traffic into the ports in 2015 and 2020, the number of vessel calls in each port from 2002 to 2007 is used to create simple linear predictions based on the data. The data are available from the U.S. Department of Transportation, which uses data from the Lloyd Maritime Intelligence Unit for the years 2002-2007 (U.S. Department of Transportation, 2009). A plot of the vessel call data and fitted linear regression lines is displayed in Figure 23. These forecasted arrival rates for each port in 2015 and 2020 are displayed in Table 30. Using the Imperfect Information-Targeted Boarding model and the forecasted arrival rates for 2015 and 2020, the required force structure is modeled using one aircraft in a directed search, 25% of the traffic in the Target set, and all other inputs set to the values in Chapter III Table 12. Each scenario

with a specific number of MOTR assets is replicated 500 times with the mean and standard error for the replication are listed in a table below their respective figures. The simulation uses the same master random number seed for each port's replication set.

The projected effects on the MOE of Miss rate based on varying number of assets for the projected arrivals in 2015 is displayed in Figure 24. The Columbia River Ports, Seattle-Tacoma, and San Francisco Bay require about two MOTR assets on patrol while Los Angeles-Long Beach requires three for a risk level of a 10% Miss Rate for the 2015 arrival rates with 25% of the traffic in the target set. For the 2020 projected data, one directed aircraft and a target set of 25% of the Total Traffic with the same input values as the 2015 case are displayed in Figure 25. Since Los Angeles-Long Beach port area is the busiest, Figure 26 displays the MOE of Miss Rate for Los Angeles-Long Beach for the projected and current traffic for various percentages of Traffic in the Target Set with the current three (current assigned minus one) MOTR Assets to conduct the 96 hour operation.

Based on these three figures, the value of limiting the target set is displayed for current assets against increasing arrivals to the port. Three cutters have a Miss Rate of less than 10% with the 2020 traffic rates if intelligence can limit the target set to 40% of the total traffic. These figures underline the need for good intelligence support to MOTR assets in the Port Regions; good intelligence limits the numbers of assets needed the operation. Other increased arrival rates could also be used to decide on force planning for seasonal increases in traffic or port infrastructure studies.

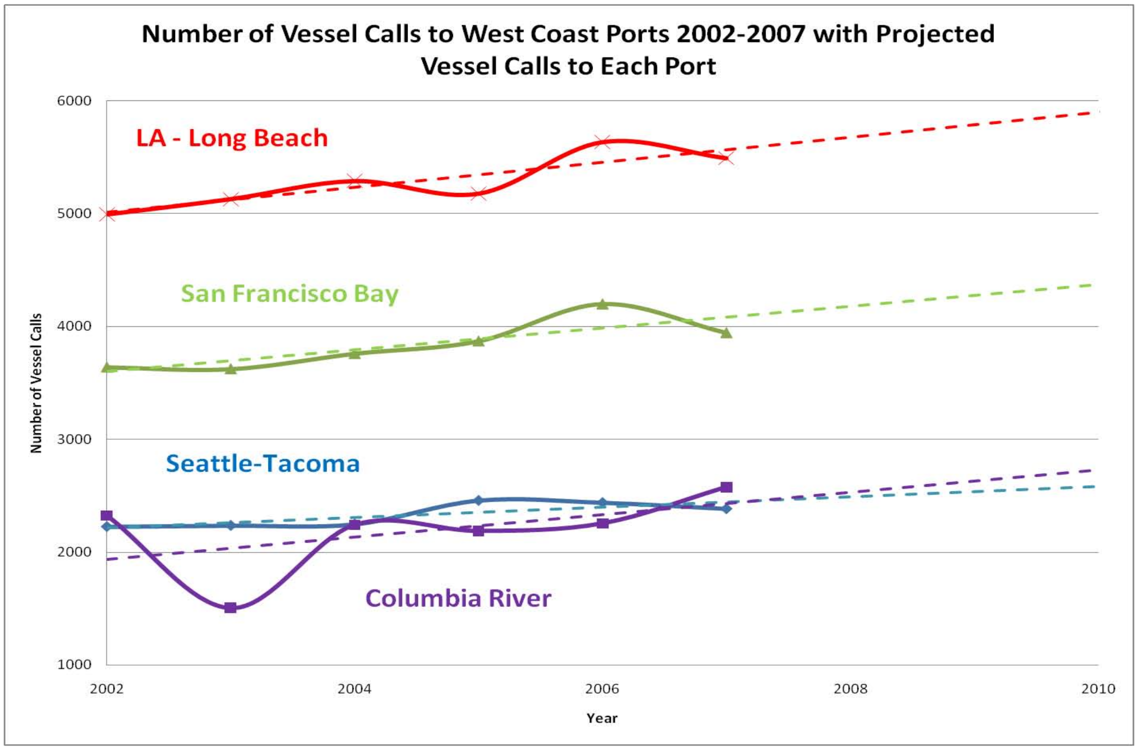

Figure 23 Number of Vessel Call on U.S. West Coast Ports from 2002 to 2007 with Predicted Linear Regression

Port	Ship / Day 2007	Ship / Day 2015	Ship / Day 2020
Seattle Tacoma	6.5	7.7	8.3
Columbia River Ports	7.1	8.8	10.2
San Francisco Bay	10.8	13.3	14.6
LA - Long Beach	15.0	17.7	19.2

Table 30 Projected Arrival Rates for the West Coast Ports in 2015 and 2020

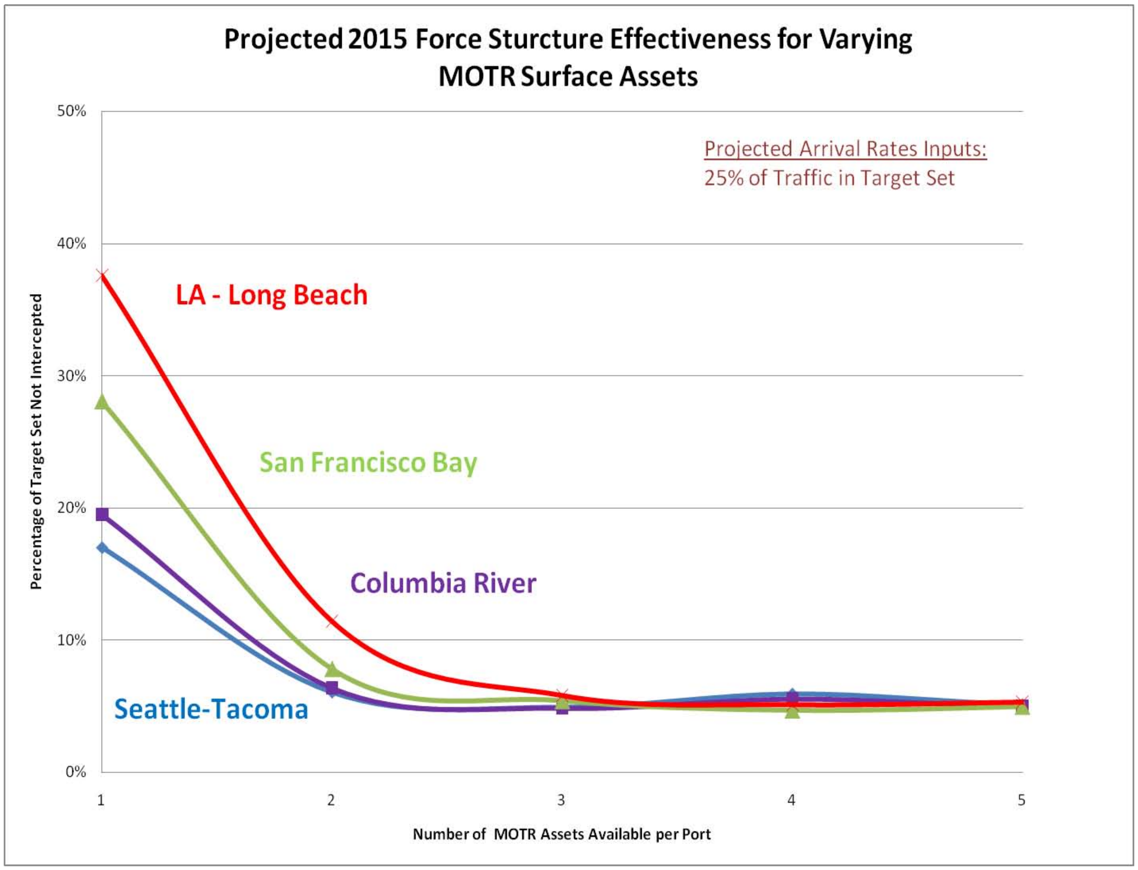

Figure 24 Projected 2015 Force Structure Effectiveness for Varying MOTR Surface Assets

Number of Assets	Seattle-Tacoma		Columbia River		San Fran Bay		LA-LB	
	Mean	Std Error	Mean	Std Error	Mean	Std Error	Mean	Std Error
1	0.170	0.006	0.195	0.006	0.281	0.006	0.376	0.005
2	0.061	0.006	0.064	0.006	0.078	0.006	0.114	0.005
3	0.049	0.006	0.048	0.006	0.054	0.006	0.058	0.005
4	0.059	0.006	0.055	0.006	0.047	0.006	0.051	0.005
5	0.051	0.006	0.050	0.006	0.050	0.006	0.053	0.005

Table 31 Means and Standard Errors for Figure 24

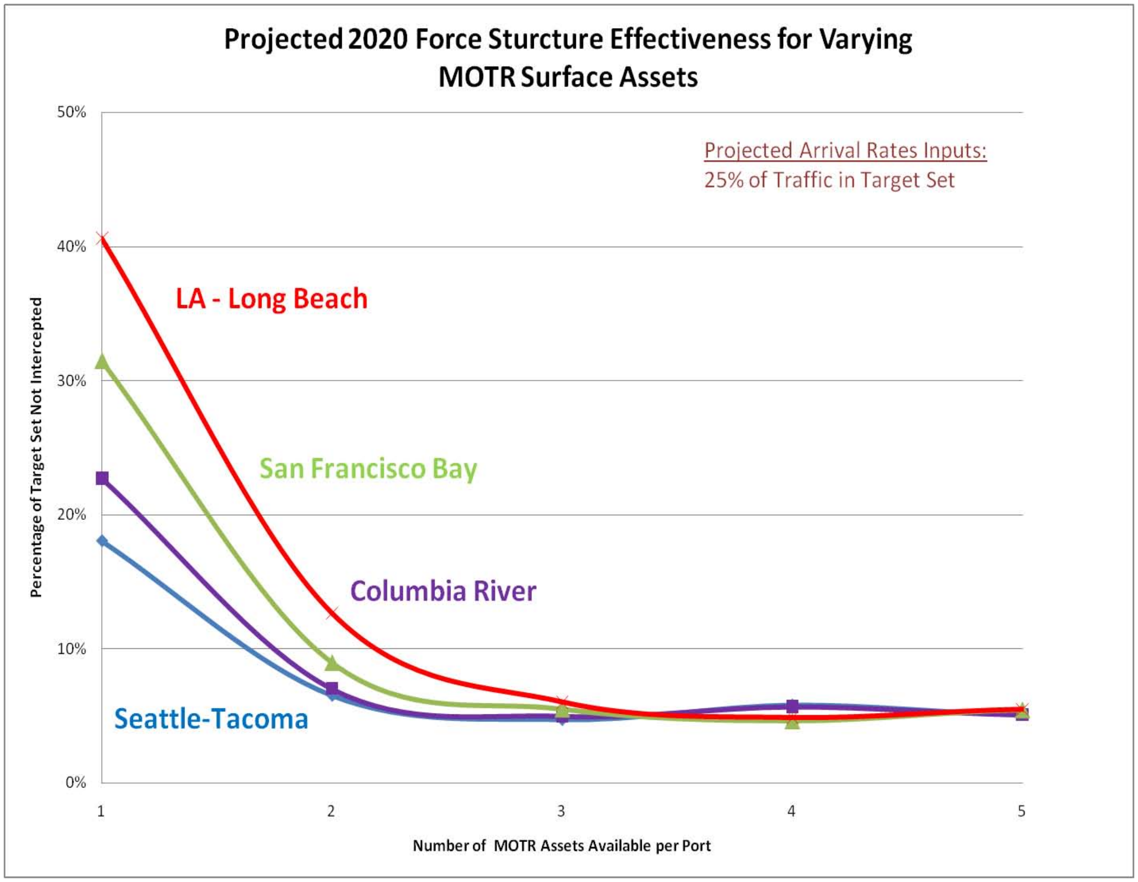

Figure 25 Projected 2020 Force Structure Effectiveness for Varying MOTR Surface Assets

Number of Assets	Seattle-Tacoma		Columbia River		San Fran Bay		LA-LB	
	Mean	Std Error	Mean	Std Error	Mean	Std Error	Mean	Std Error
1	0.181	0.006	0.227	0.006	0.315	0.006	0.406	0.005
2	0.065	0.006	0.070	0.006	0.090	0.006	0.127	0.005
3	0.047	0.006	0.050	0.006	0.055	0.006	0.060	0.005
4	0.058	0.006	0.057	0.006	0.046	0.006	0.049	0.005
5	0.051	0.006	0.051	0.006	0.055	0.006	0.055	0.005

Table 32 Means and Standard Errors for Figure 25

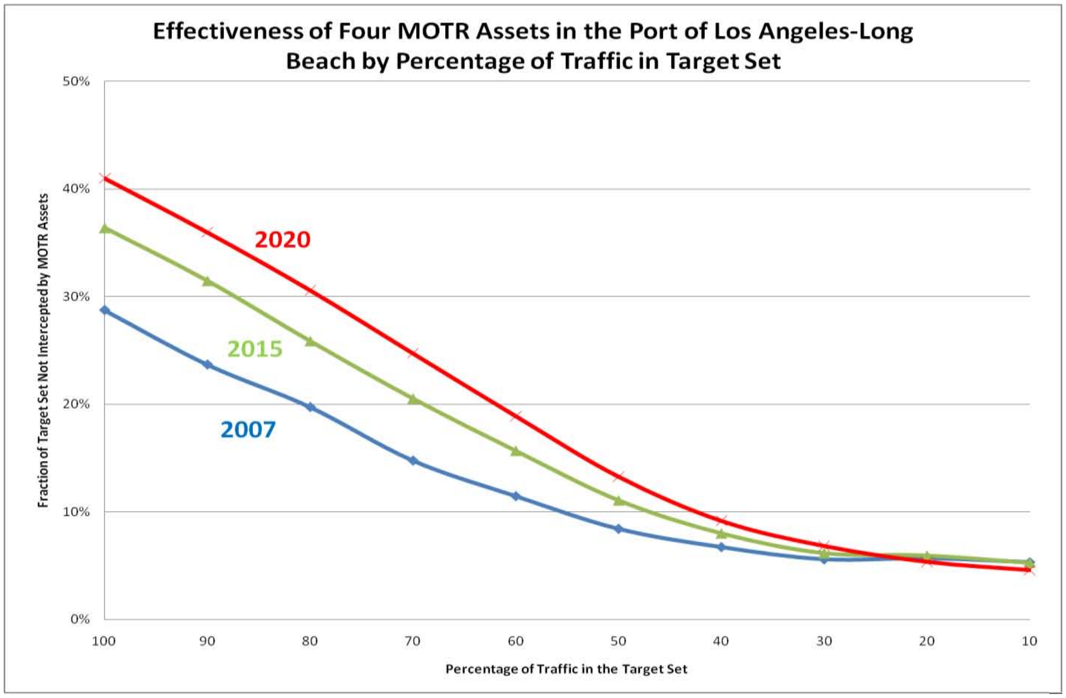

Figure 26 Effectiveness of Four MOTR Assets in the Port of Los Angeles-Long Beach by Percentage of Traffic in Target Set

Target Set %	**LA-LB 2007**		**LA-LB 2015**		**LA-LB 2020**	
	Mean	Std Error	Mean	Std Error	Mean	Std Error
10	0.053	0.005	0.052	0.006	0.046	0.006
20	0.057	0.005	0.059	0.006	0.054	0.006
30	0.056	0.005	0.061	0.006	0.068	0.006
40	0.067	0.005	0.080	0.006	0.092	0.006
50	0.084	0.005	0.111	0.006	0.133	0.006
60	0.115	0.005	0.157	0.006	0.189	0.006
70	0.148	0.005	0.205	0.006	0.247	0.006
80	0.197	0.005	0.259	0.006	0.306	0.006
90	0.237	0.005	0.315	0.006	0.360	0.006
100	0.287	0.005	0.364	0.006	0.410	0.006

Table 33 Means and Standard Errors for Figure 26

2. Vessels Less Than 300 Tons

This section uses the models to evaluate a scenario where intelligence reports a vessel less than 300 tons is carrying dangerous cargo. Vessels less than 300 tons, e.g., fishing boats, pleasure craft, coastal carriers, are not as regulated in U.S. ports. Since reliable data are not available for vessels less than 300 tons, the model arrival rates into the model are modified to reflect the number of these smaller vessels in the operating area over a 96-hour period. The actual data is not available since vessels less than 300 tons are not required to carry AIS or any tracking system. As these vessels do not have an electronic tag, aircraft would be required to identify all targets before MOTR assets board and search the suspect vessels. The average numbers of vessels in the area over a 96-hour period are varied and used to estimate a mean for the exponential inter-arrival times, which are displayed in Table 34. For example, the first arrival rate of 100 ships per 96 hours is equivalent to an arrival rate of one ship per hour. This estimation allows for an average number of vessels to pass through an area with variability equal to its mean. Using these arrival rates, a 96-hour scenario is used to assess the force structure needed to complete this type of operation. The smaller vessels are in the same 200 nm by 100 nm region, but their speed is drawn from uniform distribution between ten and twenty-five knots. Using this data and the same method described in Appendix C, parameters for Gamma distribution for the time a ship spends in the zone are estimated using MLE from the S-Plus Statistical Package (Insightful Corporation, 2007). The VBSS or board search times are modeled as random having a lognormal distribution with a mean of two hours and a standard deviation of one hour. These parameter values are informed from experience of former boarding team members. The aircraft search time parameter remains the same as previous scenarios, since the operating area's size and aircraft speed remain the same; this represents slow directed aircraft that would be organic to the MOTR sea assets. The use of data links and common operating pictures are critical to this type of mission and the use of directed aircraft to reduce search times. The simulation's distributions are displayed in Table 35.

Using these adjusted arrival rates and the Imperfect Information-Targeted Boarding Scenario the performance of four MOTR assets against a target set of 10% of

the total traffic is displayed in Figure 27. The results displayed in this figure suggest that the number of aircraft is critical to the MOE of Miss Rate, since the traffic must be classified before MOTR assets can be sent to intercept the target ship. The results of this analysis are pessimistic since the aircraft would have shorter flight durations between vessels as the number of vessels increases in the area initially, smaller vessels would spend more time in the zone since few vessels would transit across the rectangle only once; and surface platforms could also search while idle. The results also assume the aircraft and MOTR assets keep over 500 small tracks tagged correctly in a data link. This situational awareness would be very difficult to maintain in such a small area with small tracks using current technology. The key result is that the number of searching and classifying aircraft is critical to identify targeted intercepts. Without the right number of aircraft, the ships are idle waiting for red ships to board. Note that a single aircraft can be overloaded identifying all white traffic even one time. The need for small, durable, high endurance aircraft for this type of mission is critical to identify small ship traffic before a dangerous small ship penetrates internal waters. As an alternative, smaller ships could be required to carry a small AIS-like device to limit the identification problem in the ports. Some ports such as Singapore are currently requiring these devices to limit the unknown targets in waters around the Straits of Singapore (Adawiah, 2007).

Average Number of Vessels in Operating Area for a 96 hour period	**Arrival Rate (Ships per Hour)**
100	1.04
200	2.08
300	3.13
400	4.17
500	5.21

Table 34 Arrival Rates for Vessels less than 300 tons based on Average Number of Vessels in the Operating Area for a 24 period

Model Inputs	Distribution Form	Value
Number of MOTR Assets		4
Target Percentage in Target Set		10%
Boarding and Search Time (Lognormal)	$f(x;\mu,\sigma)=\frac{1}{x\sigma\sqrt{2\pi}}e^{-\frac{(\ln(x)-\mu)^2}{2\sigma^2}}$	$\mu=2,\sigma=1$
Ship Time in Zone (Gamma)	$f(x;\alpha,\beta)=\frac{1}{\beta^{\alpha}\Gamma(\alpha)}x^{\alpha-1}e^{-\frac{x}{\beta}}$	$\alpha=2.16,\beta=4.55$
Number of Aircraft		{2,4}
Search Parameter (Uniform)	$f(x)=\begin{cases}\frac{1}{b-a} & \text{for } a\le x\le b\\ 0 & \text{for } x<a \text{ or } x>b\end{cases}$	$A=0,B=1.85$

Table 35 Model Inputs for Vessel Less Than 300 Tons Simulation Model

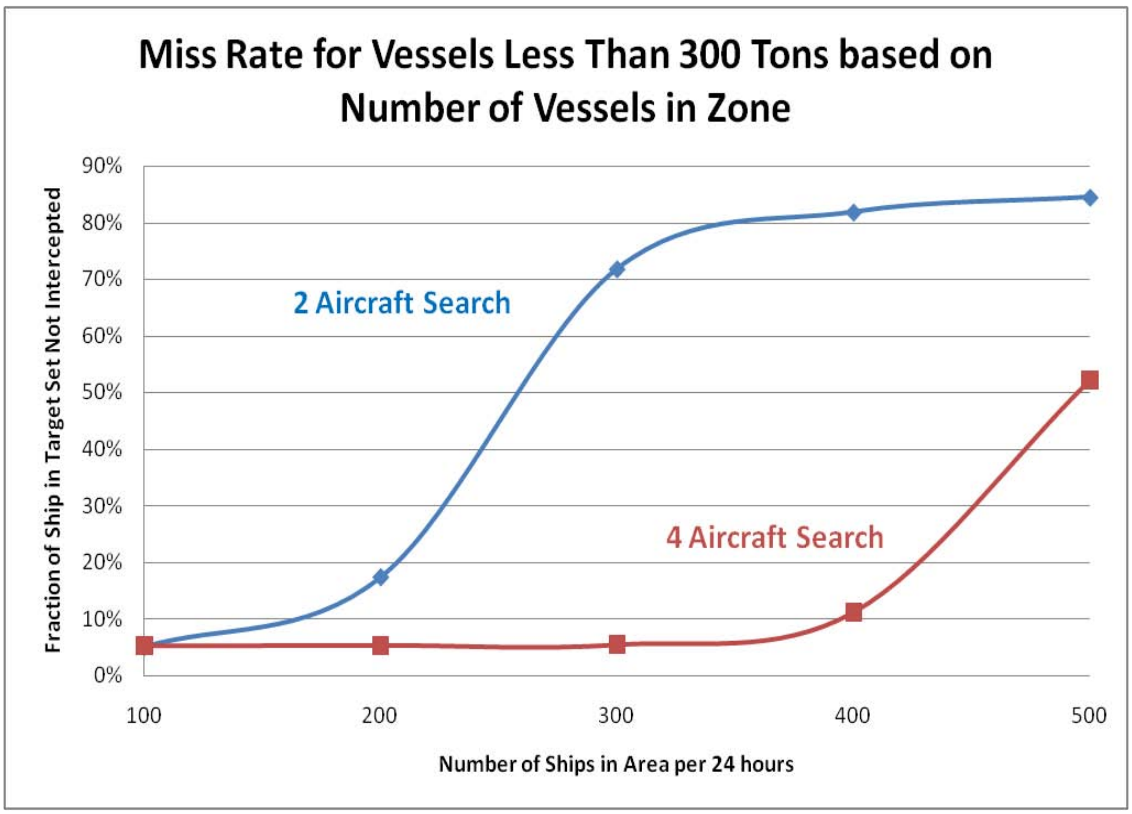

Figure 27 Miss Rate for Vessels Less Than 300 Tons by Number of Searching Aircraft and Number of Vessels in Zone per 24 Hour Period

Number of Ships in Area	2 A/C Search		4 A/C Search	
	Mean	Std Error	Mean	Std Error
100	0.050	.004	0.053	.004
200	0.174	.004	0.054	.004
300	0.718	.004	0.055	.004
400	0.819	.004	0.112	.004
500	0.845	.004	0.521	.004

Table 36 Means and Standard Errors for Figure 27

C. MODEL CAPABILITIES AND LIMITATIONS

This thesis focuses on analytical and simulations models to describe the risk versus reward resource planning for the defense of the U.S. West Coast Ports. Using these models, a user can determine the force requirements and force mix to achieve a desired level of risk in different scenarios protecting ports from dangerous threats inbound to the U.S. The risk in the models is measured by the MOE of Miss Rate, which is the average percentage of red traffic that clears the offshore "screen" and proceeds into the ports. The models provide a flexible interface to vary inputs and gain insight into force structure capability. The inputs are based on arrival rates of ships to a port, an expected time the ship can be tracked (time in the zone), the expected boarding time for surface assets, and the amount of resources that the force can commit to the operation. The model output is the surface and air assets required to meet a certain risk level. While this thesis suggested parametric distributions and parameters values for random times, another user could easily change the model distribution inputs to fit their situation. The analytical models provide instant flexibility to display general solutions quickly for planning and programming forces to the operation. This flexibility with analytical and simulation models provide the user with a tool for operational level planning for threats against the West Coast Ports.

The models have limited spatial representation. None of the models uses actual geography for intercepts or optimized search patterns to find tracks, which limit their tactical applicability. These limitations tend to result in optimistic values since geometry of the vessel's track never prevents an intercept. In addition, red traffic takes no evasive action to prevent detection or classification, which also improves performance of limited assets. In addition, aircraft search and classification is considered homogeneous and no environmental or time of day factors are included in the analysis. These limitations are notable at the tactical level but do not limit the performance of the models at the operational level.

Even with the above limitations, the models tend to be slightly pessimistic since MOTR surface assets do not conduct any search or classification of ships in any of the scenario even when idle. In reality, surface ships always maintain a radar and visual awareness. Aircraft are also limited to visual searching and classification of targets with five nm search widths for most scenarios. Improved sensor and electronic identification system would also improve a combined force's performance in the models and limit Miss Rate due to non-classification by aircraft. Lastly, the process of boarding and searching a target ship from MOTR assets based on previous experience and other scientific papers was used to suggest a reasonable parametric distribution for the time spent boarding and searching a ship; improved sensor and tools improve the ability to search a ships and their cargo. This set of models provides the user with a flexible tool determine risk versus reward while defending the West Coast Ports.

VI. CONCLUSIONS AND FUTURE WORK

A. CONCLUSIONS

This thesis focused on the problem of intercepting a ship traveling to the major West Coast Ports prior to reaching the Territorial waters of the United States. The focus was a risk versus reward utilization of limited MOTR surface and air assets available to conduct the mission. This operation assumes there is prior intelligence, which limits vessels of interest to a subset of all traffic entering the ports. In the general scenario, aircraft are used to identify and classify tracks prior to interception by surface forces. Risk is measured by the economic impact or the time shipping is delayed to the port when all traffic must be boarded by assets, or by the percentage of traffic in the target set which proceeds to port without interception by a surface asset in the general case. Both analytical and simulation models are formulated to determine the risk based on varying values of MOTR assets and percentage of traffic in the target set with parametric distributions of the random times in the simulations to explore the range of values associated with this type of operation.

The results of the thesis suggest that USCG assets used for maritime intercept operations are not sufficient to protect the West Coast Port from incoming large ships. Other MOTR stakeholders need to support USCG forces in this type of operation. The USCG require additional surface ship assets in all port areas or increased intelligence sharing to reduce the target set of ships of interests so current USCG ships and their organic air assets can complete this maritime interception operation (MIO). The scenarios in this thesis restricted the MIO to ships that arrive during a 96-hour period; the restriction limits logistic requirements. However, if maritime intercept operations continue for a prolonged time, then logistic considerations require that additional forces are needed to maintain a number of surface and air assets to complete the MIO mission at an acceptable risk. The need for high-endurance air assets with long on-station times and the ability to be directed by sea or land assets is critical to this operation, since the ability of aircraft to identify and classify all traffic limits the number of MOTR assets needed to complete the MIOs. The capability to identify correctly the accurate subset of the traffic

consisting of ships of interest prior to the operation and the correct classification of all ships using aerial vehicles during the mission is critical to reduce MOTR surface asset participation. In addition, specific training of personnel and procurement of search equipment is required to reduce the number of surface assets required to complete these missions. Lastly, ship traffic and the size of vessels to the U.S. coastal ports continue to increase (Mercator Transport Group, 2005). Hence, enemy exploitation of incoming ships to U.S. ports continues to represent a vulnerability to the U.S. economy and citizens. This thesis underlies the need for accurate and timely intelligence sharing, flexibility in asset cooperation amongst stakeholders, and the ability to execute a joint / interagency operation in a short time.

The models are flexible tool for determining the resources needed to protect U.S. West Coast ports based on variable risk. The models represent the critical inputs, platforms, and tactics currently employed by MOTR forces for this mission. The models can quickly evaluate current and future force structure to deter and intercept dangerous cargo into the United States based on variable risk levels. The models also have the flexibility to evaluate platform and technology value added to the general mission. These models provide an operational level commander a baseline tool to conduct port defense maritime intercept operations.

B. FUTURE WORK

This thesis is a first attempt to assess resources needed for maritime intercept operations and larger problems in Maritime Domain Awareness and Port Defense. The models and simulations developed in this thesis describe the scenario in averages and do not explore the edges of the operations where vulnerabilities might be present. While the models provide good estimates for the operational level, they are not sufficient for the tactical level. In the development of the Search and Detection sections of this model, a variety of simplifications makes this the area of concern for a tactical user. Aircraft did not use optimized search patterns for their sensors and no electronic means for detection or classification were considered. Also, no overhead assets detecting and classifying ships entering the area were considered in the search and detection sections. Additional

work at the tactical level for intercept geometry was not considered in the development of MOTR assets locations and it was assumed if a red ship was still in the zone and a cutter was idle that the intercept would be possible. Future work could also compare the operational level assumptions in these models with similar MOE values calculated by using a large-scale spatial simulation such as Naval Simulation System (NSS) (Metron Corporation, 2008).

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APPENDIX A.

A. BASIC QUEUING MODEL

1. Minimal Information-100% Inspection Mathematical Model

The Mathematical Model for this case is developed from a multiple server queuing model with an infinite waiting room. The target ships arrive according to a Poisson process with rate λ; the queue is processed in a First Come – First Serve discipline (FIFO). The service times are assumed to be independent and identically distributed (i.i.d.) having an exponential distribution with mean $1/\mu$ where the service time includes the time to board and search the vessel. The critical MOEs for this model are the Average Number in the Queue $\left(L_q\right)$ and the Average Time in the System (W). The equations for this scenario are based on Steady-State Results for a Multiple Server Single Stage Queue, which appears in equations (1)-(4). It is assumed the server utilization factor ρ is less than one, see *Ross* (Ross, 2007).

$$\rho = \frac{\alpha}{M\mu} \tag{1}$$

$$\pi_0 = \left(\sum_{i=0}^{M-1} \frac{(\rho M)^i}{i!} + \frac{(\rho M)^M}{M!(1-\rho)} \right)^{-1} \tag{2}$$

$$\begin{aligned} L_q &= \pi_0 \frac{M^M \rho^{M+1}}{M!(1-\rho)^2} \\ L &= L_q + \frac{\lambda}{\mu} \end{aligned} \tag{3}$$

$$W = \frac{L}{\lambda} \tag{4}$$

B. BIRTH DEATH MODELS

1. Good Information-Intelligent Boarding Birth Death Model

The Perfect Information-Intelligent Boarding Analytical Model is a Birth Death Model (Ross, 2007). For this case, let $R(t)$ be the number of suspicious ships in the region at time t. The suspicious ships arrive according to Poisson Process with rate α. There are c intercept units that intercept and board ship with i.i.d. times having an exponential distribution with rate μ. The times that a suspicious ship spends in the region are i.i.d. having an exponential distribution with rate λ. Then the probability a ship arrives to the region is given in Equation 5, and the probability a ship is boarded is dependent on how many ships and interceptors are in the region given by Equations 6 and 7. The split between Equations 6 and 7 is determined if more ships are available to board than total number of interceptors where r is the number ships and c is the number of interceptors.

$$P\left\{R(t+h)=r+1 \mid R(t)=r\right\}=\alpha h+o(h) \tag{5}$$

$$P\left\{R(t+h)=r-1 \mid R(t)=r\right\}=\min(r,c)\mu h+o(h) \quad \text{for } r \le c \tag{6}$$

$$P\left\{R(t+h)=r-1 \mid R(t)=r\right\}=\left[c\mu+(r-c)\lambda\right]h+o(h) \quad \text{for } r > c \tag{7}$$

From these equations a set of limiting probabilities or the probability r ships are in the area can be obtained are displayed in Equation 8. These limiting probabilities are dependent on the number of ships and interceptors in the region and the equations based on the number interceptors available to board the number of ships. Using these limiting probabilities, the long run average number of ships that pass through the region without being boarded (L) is obtained and displayed in Equation 11. Using Equation 11 and the arrival rate the MOE, Miss Rate or Fraction of ships in the target set not intercepted by MOTR assets, can be calculated using Equation 12, where p_r is the percentage of the total traffic that is in the target set. To compare the miss rate in equation 12 to the simulation results Equation 12 is multiplied by the length of the miss, e.g., 96 hours.

$$\pi(r) = \lim_{t \to \infty} P\left(R(t) = r \mid R(0) = r_0\right) \tag{8}$$

$$\pi_r = \pi_0 \frac{1}{r!}\left[\frac{\alpha}{\mu}\right]^r \text{ for } r \le c \tag{9}$$

$$\pi_r = \pi_0 \frac{1}{c!}\left[\frac{\alpha}{\mu}\right]^c \prod_{k=c+1}^{r} \frac{\alpha}{c\mu + (k-r)\lambda} \quad \text{for } r > c \tag{10}$$

$$L = \sum_{r=1}^{\infty} \pi_r \left[r - c\right]\lambda \tag{11}$$

$$\text{Miss Rate} = \frac{L}{\alpha} p_r \tag{12}$$

2. Imperfect Information- Intelligent Boarding Birth-Death Model

The Imperfect Information-Intelligent Boarding Analytical Model is based on a Birth Death Model (Ross, 2007). This model uses an aircraft to classify targets before the ships are intercepted. In this case, there is one aerial vehicle classifying ships in the region. Let c_{ww} and c_{rr} be the conditional probabilities that white ship is classified as white and that a red ship is classified as red. Let p_r be the percentage of total traffic that in the target set (red). The time until a ship classified by an aerial vehicle has an exponential distribution with rate δ_A. The arrival rate of ships in the target set can be calculated by using Equation 13 to get the arrival rate of red ships to the region.

For this case, let $S(t)$ be the number of ships in the region at time t that have been classified as suspicious by the aircraft. These suspicious ships arrive according to Poisson Process with rate α_B. There are c intercept units that intercept and board ship with i.i.d. times having an exponential distribution with rate μ. The times that red ships spend in the region are i.i.d. having an exponential distribution with rate λ. The probability a red ship arrives to the region in the time interval (t, t+h] is given in Equation 14. The

probability a red ship is boarded in the time interval (t, t+h] is dependent on how many ships and interceptors are in the region and is given by Equations 15 and 16. The difference between Equations 15 and 16 is due to more ships being available to board than total number of interceptors where *r* is the number ships and *c* is the number of interceptors.

$$\alpha_B = \alpha \frac{\delta_A}{\delta_A + \lambda} \left\{ p_R c_{rr} + \left(1 - p_R\right)\left(1 - c_{ww}\right) \right\} \tag{13}$$

$$P\left\{ S\left(t+h\right) = r+1 \mid S\left(t\right) = r \right\} = \alpha_B h + o\left(h\right) \tag{14}$$

$$P\left\{ S\left(t+h\right) = r-1 \mid S\left(t\right) = r \right\} = \min\left(r,c\right)\mu h + o\left(h\right) \quad \text{for } r \le c \tag{15}$$

$$P\left\{ S\left(t+h\right) = r-1 \mid S\left(t\right) = r \right\} = \left[c\mu + \left(r-c\right)\lambda \right] h + o\left(h\right) \quad \text{for } r > c \tag{16}$$

From these equations, a set of limiting probabilities for the number of suspicious ships that are in the area is given by Equation 17. These limiting probabilities are dependent on the number of ships and interceptors in the region. Using these limiting probabilities the long run average number of suspicious ships that pass through the region without being boarded $\left(L_N\right)$ is calculated and displayed in Equation 20. Using Equations 21, 22 and 23, the three major parts of the Miss Rate MOE are calculated, LA is the long run average number of Red ships not classified by an aircraft, LB is the long run average number of ships classified correctly and not intercepted by MOTR Assets, and LC is the average number of red ships classified incorrectly. Taking the sum of the previous three equations, Equation 24, displays the long run average number of red ships that pass through the region without being boarding. The long run average Miss Rate is computed from this sum and the red ship arrival rate in Equation 25. To compare this miss rate to the average number of ship missed in the simulation the miss rate is multiplied by the mission time, e.g., 96 hour.

$$\pi(r) = \lim_{t\to\infty} P\big(R(t) = r \mid R(0) = r_0\big) \tag{17}$$

$$\pi_r = \pi_0 \frac{1}{r!}\left[\frac{\alpha_B}{\mu}\right]^r \text{ for } r \le c \tag{18}$$

$$\pi_r = \pi_0 \frac{1}{c!}\left[\frac{\alpha_B}{\mu}\right]^c \prod_{k=c+1}^{r} \frac{\alpha_B}{c\mu + (k-r)\lambda} \quad \text{for } r > c \tag{19}$$

$$L_N = \sum_{r=1}^{\infty} \pi_r [r-c]\lambda \tag{20}$$

$$L_A = \alpha\left[\frac{\lambda}{\lambda + \delta_A}\right] p_R \tag{21}$$

$$L_B = L_N \frac{p_R c_{rr}}{p_R c_{rr} + (1-p_R)(1-c_{ww})} \tag{22}$$

$$L_C = \alpha\left[\frac{\delta_A}{\lambda + \delta_A}\right] p_R (1-c_{rr}) \tag{23}$$

$$L = L_A + L_B + L_C \tag{24}$$

$$\frac{L}{\alpha p_R} \tag{25}$$

C. FLUID MODEL

The Fluid Model is an analytical representation of the Imperfect Information-Targeted Boarding Case. The Fluid Model represents the ships and cutters as fluids and not individual entities which results in fractional losses of ships which can causes this model to predict lower numbers of losses than the simulation with exponential distributions for random times. This phenomenon is discussed further in Chapter IV,

which compares the simulation and analytical models. This fluid model can also be adjusted to the Perfect Information Case by decreasing the aircraft search time to a very small value and increasing the number of aircraft to a large value. The model can represent aircraft conducting either directed or undirected search by specifying the mean of the distribution of the search time and the number aircraft available; for example, a very large number of aircraft approximates the undirected searching aircraft case.

Suppose two types of ships enter a region: Friendly (White, *W*) ships and suspicious ships (Red, *R*). The ships are in the region and subject to boarding for a finite time. Aircraft perform an initial classification of ships as *W* or *R* with error. Ships classified as *R* are boarded. A measure of performance is the rate at which ships *R* ships pass through the region without being intercepted by a MOTR Assets. This is the sum of three different possibilities for *R* ships to pass through the region without boarding. First, an *R* ship may not be classified by an aircraft before leaving the region. Second, an *R* ship may be classified correctly but an MOTR assets or intercept ships is not available to board the *R* ship prior to it leaving the region. Last, an *R* ship may be classified incorrectly as *W* and pass through the region with being intercepted. The number of ships in each of these cases is calculated in the Fluid Model using the following symbols L_A, L_B, and L_C, respectively.

Variables:

$U(t) =$ Mean number of unidentifed vessels in the region at time t
$S(t) =$ Mean number of vessels classified as suspicious in the region at time t
$B_A(t) =$ Mean number of aircraft busy at time t
$B_B(t) =$ Mean number of boarding parties busy at time t
$L_A(t) =$ Mean number of Red ships that travel through the region during $(0, t]$ without being classified by an aircraft
$L_B(t) =$ Mean number of Red ships that travel through the region during $(0, t]$ that have been classifeid correctly but travel through the region before being boarded
$L_C(t) =$ Mean number of Red ships that travel through the region during $(0, t]$ that have that have been classified incorrectly
$L(t) =$ Mean number of Red ships that travel through the region unboarded during $(0, t]$

Parameters:

$\alpha =$ Arrival rate of ships to the region

$p_R =$ Probability a ship is member of the target set

$\frac{1}{\delta_A}$ = Mean time for aircraft to travel to ships

$\frac{1}{\delta_B}$ = Mean time for boarding team to travel to ships

$\frac{1}{\beta_A}$ = Mean time for aircraft to classify a ship

$\frac{1}{\beta_B}$ = Mean time to board and search a ship

M_A = Number of Aircraft

M_B = Number of Boarding Parties

$\frac{1}{\lambda}$ = Mean time a ship is subject to classification and boarding; (time in zone)

$c_{ww} =$ Conditional probability a White ship is classifed as W by aircraft; $c_{wr} = 1 - c_{ww}$

$c_{rr} =$ Conditional probability a Red ship is classifed as R by aircraft; $c_{rw} = 1 - c_{rr}$

Equations:

$$\underbrace{\frac{dU(t)}{dt}}_{\substack{\text{Change in the}\\ \text{number of unclassifed}\\ \text{ships in the region}}} = \underbrace{\alpha}_{\substack{\text{Arrival rate}\\ \text{of ships}}} - \underbrace{\delta_A\left[M_A - B_A(t)\right]^+ U(t)}_{\text{Rate Aircraft are directed to travel to ships}} - \underbrace{\lambda U(t)}_{\substack{\text{Rate ships leavethe region}\\ \text{without classification}}}$$

$$\frac{dS(t)}{dt} = \underbrace{\beta_A B_A(t)\left[\left[1-p_R\right]c_{wr} + p_R c_{rr}\right]}_{\text{Rate ships are classified Suspicious}} - \underbrace{\lambda S(t)}_{\substack{\text{Rate suspicious ships}\\ \text{leave the region}\\ \text{without being boarded}}} - \underbrace{\left[M_B - B_B\right]^+ \delta_B S(t)}_{\text{Rate of suspicious ships being boarded}}$$

$$\frac{dB_A(t)}{dt} = \underbrace{\delta_A\left[M_A - B_A(t)\right]^+ U(t)}_{\text{Rate Aircraft are directed to travel to ships}} - \underbrace{\beta_A B_A(t)}_{\substack{\text{Rate of completion}\\ \text{of classification}}}$$

$$\frac{dB_B(t)}{dt} = \underbrace{\delta_B\left[M_B - B_B(t)\right]^+ S(t)}_{\substack{\text{Rate at which suspicious ships}\\ \text{are boarded}}} - \underbrace{\beta_B B_B(t)}_{\substack{\text{Rate of completion}\\ \text{of boardings}}}$$

$$\frac{dL_A(t)}{dt} = \lambda U(t)\, p_R$$

$$\frac{dL_B(t)}{dt} = \lambda S(t) \frac{p_R c_{rr}}{p_R c_{rr} + (1-p_R)c_{wr}}$$

$$\frac{dL_C(t)}{dt} = \beta_A B_A(t)\, p_R c_{rw}$$

$$L(t) = L_A(t) + L_B(t) + L_C(t)$$

where $x^+ = \max(x, 0)$.

D. AN APPROXIMATE M/G/1 QUEUING MODEL

An approximate M/G/1 Queuing Model is developed to compare the results of the simulation and fluid model to the specific case of one boarding unit. This model does allow ships to move through the region as fractions or parts and better represents the operation. This M/G/1 model development is based on work done in *Modeling and Analysis of Uncertain Time-Critical Tasking Problems* (Gaver, Jacobs, Samorodnitsky, & Glazebrook, 2006).

Assume there is one boarding party. It is assumed suspicious ships arrive according to a Poisson Process with rate α_B defined by Equation 26. The time until an aircraft classifies a ship has an exponential distribution with mean $\frac{1}{\delta_A}$; α is the arrival

rate of the Poisson process representing the arrivals of ships to the region. A ship is in the target set with probability p_R independently from ship to ship; each ship spends an exponential length of time with mean $\frac{1}{\lambda}$ in the region. The conditional probabilities of correct classification are c_{ww} and c_{rr} as before. The service time for a suspicious ship is given in Equation 27 where T_B is the time for a boarding party to travel to the ship is and S_B is the VBSS time. The Laplace transform of the service time for suspicious ship is then Equation 28.

$$\alpha_B = \alpha \frac{\delta_A}{\delta_A + \lambda}\left[\left[1 - p_R\right] c_{wr} + p_R c_{rr}\right] \tag{26}$$

$$C = \begin{cases} 0 & \text{if the boarding party cannot travel to a ship before ship leaves the region} \\ T_B + S_B & \text{with Probability:} \quad e^{-\lambda T_B} \end{cases} \tag{27}$$

$$\begin{aligned} E\left[e^{-sC}\right] &= E\left[1 - e^{-\lambda T_B}\right] + E\left[e^{-\lambda T_B} e^{-s\left[T_B + S_B\right]}\right] \\ E\left[C\right] &= E\left[e^{-\lambda T_B}\left[T_B + S_B\right]\right] \end{aligned} \tag{28}$$

We assume a suspicious ship is boarded with probability p independent of the other ships. The Pollaczek-Khinchine (P-K) formula for M/G/1 queues yields the transform of the virtual waiting time in queue displayed in Equation 29. On the other hand, the probability an arriving suspicious ship is boarded is given in Equation 30. $B(p)$ in Equation 30 follows from Equation 29 and is decreasing in p on [0, 1/p] and is always between 0 and 1. Hence, Equation 30 always has a unique solution $\tilde{p}$ which satisfies the quadratic equation in this case. The approximation for the probability a suspicious ship is not lost while waiting for a boarding party to become available is displayed in Equation 31.

$$E\left[e^{-sW}\right]=\frac{1-p\alpha_B E[C]}{1-p\alpha_B\left[\frac{1-E\left[e^{-sC}\right]}{s}\right]} \tag{29}$$

$$p=E\left[e^{-\lambda W}\right]=\frac{1-p\alpha_B E[C]}{1-p\alpha_B\left[\frac{1-E\left[e^{-\lambda C}\right]}{\lambda}\right]}\equiv B(p) \tag{30}$$

$$\psi(\lambda)=E\left[e^{-\lambda W}\right]=\frac{1-\tilde{p}\alpha_B E[C]}{1-\tilde{p}\alpha_B\left[\frac{1-E\left[e^{-\lambda C}\right]}{\lambda}\right]} \tag{31}$$

The long run average rate which ships get boarded, the long run average number of suspicious ships are lost, and the long run average number of Red ships that are lost after identification but prior to boarding are all given in Equations 32, 33, and 34 respectively. The approximate average number of Red ships lost after identification but prior to boarding during 96 hours is given in Equation 35.

$$\alpha_B\psi(\lambda)E\left[e^{-\lambda T_B}\right] \tag{32}$$

$$\alpha_B\left[1-\psi(\lambda)E\left[e^{-\lambda T_B}\right]\right] \tag{33}$$

$$r_B=\alpha_B\left[1-\psi(\lambda)E\left[e^{-\lambda T_B}\right]\right]\frac{p_R c_{rr}}{p_R c_{rr}+(1-c_{ww})(1-p_R)} \tag{34}$$

$$L_B=r_B\cdot 96 \tag{35}$$

For the case in Chapter IV, T_B, the time for a boarding party to travel to the ship, has an exponential distribution with rate δ_B and S_B, the time for boarding and search of

the ship, has an exponential distribution with a rate β and all times are independent. For this case, the expected equations for these assumptions above are displayed below.

$$E\left[e^{-sT_B}\right]=\frac{\delta_B}{\delta_B+s};\quad E\left[e^{-sS_B}\right]=\frac{\beta}{\beta+s}$$

$$E\left[T_B e^{-sT_B}\right]=\int_0^\infty te^{-st}\delta_B e^{-\delta_B t}dt=\frac{\delta_B}{\left[\delta_B+s\right]^2}$$

$$E[C]=E\left[e^{-\lambda T_B}\left[T_B+S_B\right]\right]=\frac{\delta_B}{\left[\delta_B+\lambda\right]^2}+\left[\frac{\delta_B}{\delta_B+\lambda}\right]\frac{1}{\beta}$$

$$E\left[e^{-sC}\right]=1-E\left[e^{-\lambda T_B}\right]+E\left[e^{-(\lambda+s)T_B}\right]E\left[e^{-sS_B}\right]$$

$$=1-\frac{\delta_B}{\delta_B+\lambda}+\left[\frac{\delta_B}{\delta_B+\lambda+s}\right]\left[\frac{\beta}{\beta+s}\right]$$

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APPENDIX B.

A. ARENA SOFTWARE TOOL

The Arena software tool is flexible simulation software tool that allows users to represent complicated system in a graphical flow chart and analysis modules (Kelton, 2007). Arena has application in healthcare, business, and national defense and has been used in several NPS theses in the area of homeland defense including Container Port Simulation used as reference for this thesis (Pidgeon, 2008). The three Arena models developed for this thesis are explained in detail in this appendix.

B. ARENA SIMULATIONS

Three specific simulations were developed to study the risk versus reward for the defense of the U.S. West Coast Ports. All three simulations have some inputs in common listed below in the Global parameters. These inputs for the simulations are described in detail in Chapter II, but are repeated below in Table 37 as reference. The distributions, parameters for those distributions, and for the other inputs are discussed in detail in Chapter III and are referred to generally in this appendix.

Port Zone	**Arrival Rate (ships / hr) [λ]**	**Average Number of Hours between ship arrivals [1/λ]**	**Baseline MOTR Assets**
Seattle-Tacoma	0.27	3.7	3
Portland	0.29	3.4	2
Oakland	0.45	2.2	3
Los Angeles-Long Beach	0.63	1.6	4

Table 37 List of Scenario Common Data

1. Minimal Information-100% Inspection Simulation Model

The Minimal Information-100% Board Scenario simulation was built in the Arena Modeling Software Tool by Rockwell Software (Rockwell Software Inc., 2005). Arena creates entities and moves these entities through modules to simulate the functions. Each entity can carry certain information of properties called Attributes in Arena. Below in Figure 28 is the Arena Screenshot for the No Information Model, since all ports are shown, we focus on the top set of boxes for the Port of Seattle-Tacoma.

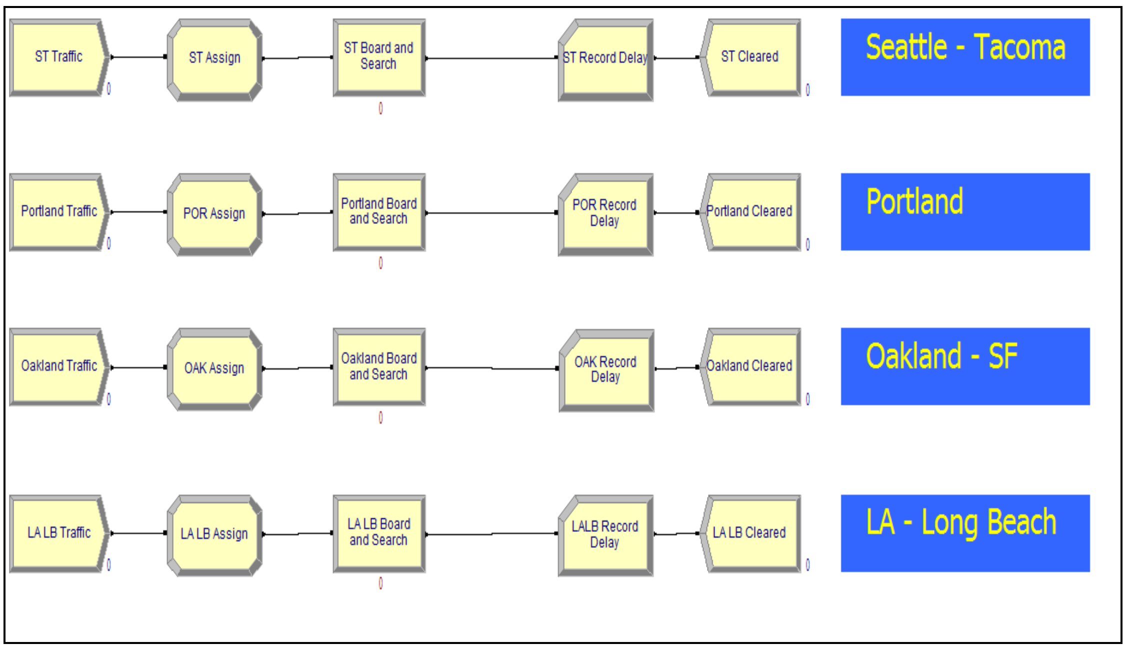

Figure 28 No Information Arena Model Screenshot

Arena creates Ship entities as inbound traffic to the port in the module *ST Traffic*, and the time between arrivals are randomly drawn from an Exponential Distribution. Next the ship entities move along the line to *ST Assign* module where they are given attributes for later data analysis. Next, the ship entities enter a process module, *ST Board and Search*, where they interact with a boarding team resource for the random time drawn from a distribution. The ship entities are then counted and their time spent in the system is calculated by the next module, *ST Record Delay*, and disposed of in the last module ST Cleared.

The Arena Simulation allows the limiting of the boarding party workday to 14 hours to measure how busy the boarding teams are during the period. The Measures of Effectiveness (MOEs) for the simulation are the total delay or time in system of the ship. The Average Total Delay for the ship gives the amount of time the Port is idle waiting for traffic while the Boarding Team Utilization measures what percentage of the workday the boarding team is occupied doing the MIO operations. For the simulation, only ships that enter and leave the simulation are considered for the MOE calculation.

Input	**Description**
Arrival Rates	Time between Arrivals to the Port
Board and Search Time	Time to Board and Search a Vessel

Table 38 Inputs to the No Information-100% Boarding Simulation

2. Good Information-Targeted Boarding Simulation Model

The Good Information-Targeted Boarding Scenario simulation was built in the Arena Modeling Software Tool by Rockwell Software (Rockwell Software Inc., 2005). The Arena Block diagram is shown below in Figure 29 and can be divided into two distinct parts: ship and interceptor. This figure only shows the Port of Seattle-Tacoma since all four ports have identical block diagrams only different parameters. Target ship and interceptor entities move instantaneously between modules unless the module has a specific delay assigned to it. The delays are random times generated from distribution input from the user prior to the simulation run.

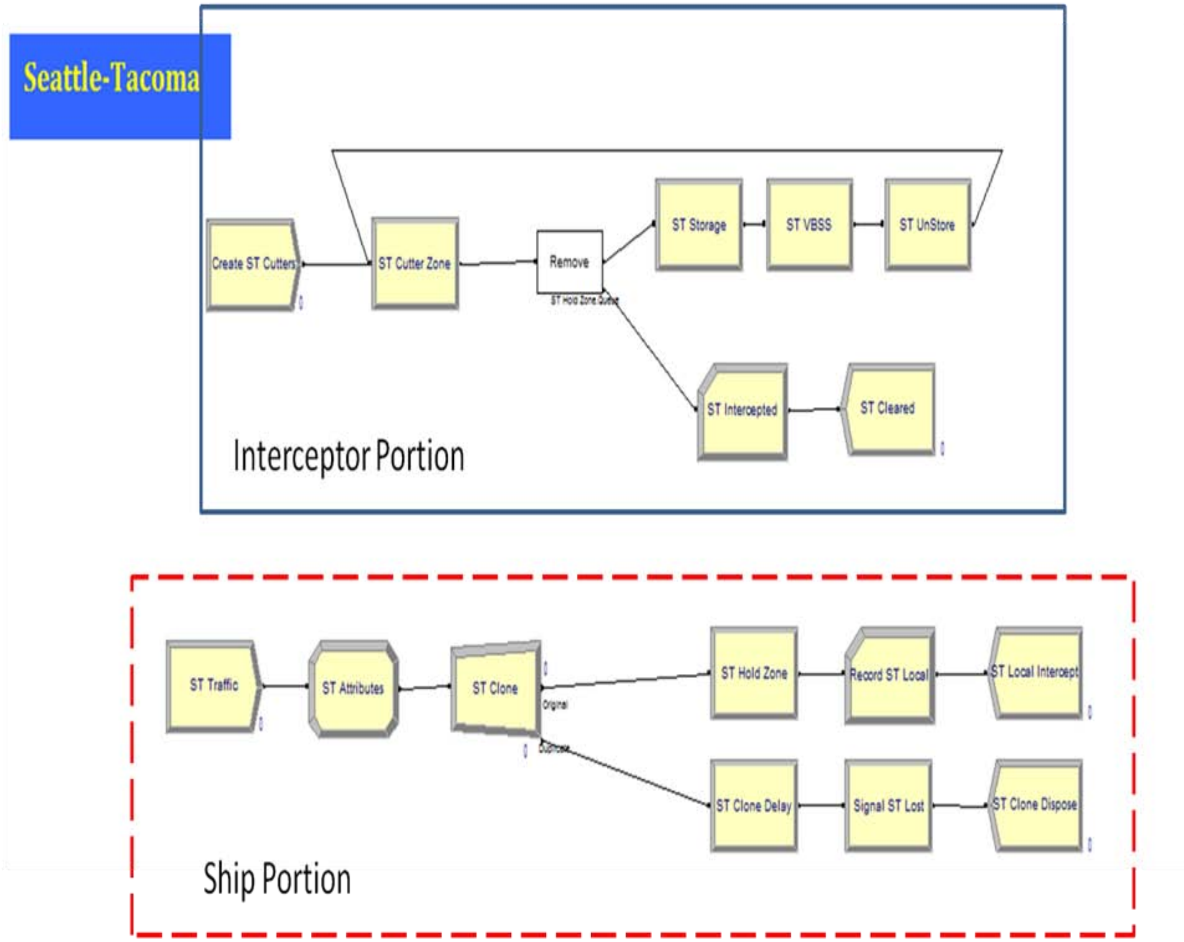

Figure 29 Perfect Information-Intelligent Boarding Arena Screenshot

The top portion of Figure 29 or the Interceptor Portion is where the required numbers of interceptor entities are created for the model according to scenario, in the *Create ST Cutters* box. The interceptors then move to *ST Cutter Zone*, which is a holding queue and stays there until there is a target set ship available to be boarded. Once a target set ship arrives to the *ST Hold Zone* box, a queuing module, in the Ship Portion of model, the interceptor entity is released from the queue and moves to the *Remove* module. At the *Remove* module, a target ship entity is lifted from the *ST Hold Zone* box and moves to the *ST Intercepted Module* where it is counted and then disposed of in *ST Cleared*. The interceptor moves to the *ST VBSS* module in the upper part of the split, the *ST Storage* and *ST UnStore* modules are only for animation purposes. At the *ST VBSS* module, the interceptor is delayed a random time drawn from a distribution; this simulates the VBSS

time and the time for the interceptor to close the ship for boarding. Once the interceptor is complete with this delay it goes back to the *ST Cutter Zone* module where it waits for another ship arrive or removes the first ship in the queue if present.

The bottom portion of Figure 29 or the ship Portion is where target set ship entities arrive to the simulation with the time between arrivals drawn from an exponential distribution. Each target set ship is given attributes in the *ST Attributes* module, including a unique serial number and ship time in zone, which is a random time drawn from a distribution. Next, the target set ship is cloned in the *ST Clone* module as a process so that the model can allow some ships to leave the zone. Then the target set ship is placed in the queue for either interceptor removal described above, or its Clone's signal. The Clone ship has the same unique serial number and is delayed for a time based on the time in zone attribute assigned in an earlier module. When the clone's time delay is complete it moves to the *Signal ST Lost* module where it sends the unique serial number to the *ST Hold Zone* module where the ship with the same serial number is released. Once the original ship is released, it is counted and then disposed, while the clone is disposed once it completes signal module. If the target ship is not present when its clone reaches the signal module, the clone is disposed of with no other action.

The model's key MOE is Miss Rate or the fraction of ships in the target set not intercepted by MOTR assets, but other data can be collected including average delay at the interceptor queue, and the average number of interceptors in the queue. The Miss Rate only considered target set ships that have entered and left, by boarding or clone signal, the simulation for the scenario time.

Input	Description
Arrival Rates	Time between Arrivals to the Port
Board and Search Time	Time to Board and Search a Vessel
Ship Time in Zone	Time a Ship is available for Boarding and Search

Table 39 Good Information-Targeted Boarding Input Parameters for Arena Simulation

3. Imperfect Information-Targeted Boarding Simulation Model

The Imperfect Information-Targeted Boarding simulation was built in the Arena Modeling Software Tool by Rockwell Software (Rockwell Software Inc., 2005). This simulation includes aircraft and aircraft classification variables into the software. The simulation can be broken into three portions: the aircraft identification, interceptor, and ship/ clone. Each section represents the major processes in the simulation models. The entire model with the three portions is displayed in Figure 30. Each portion's screenshot is displayed with its respective section.

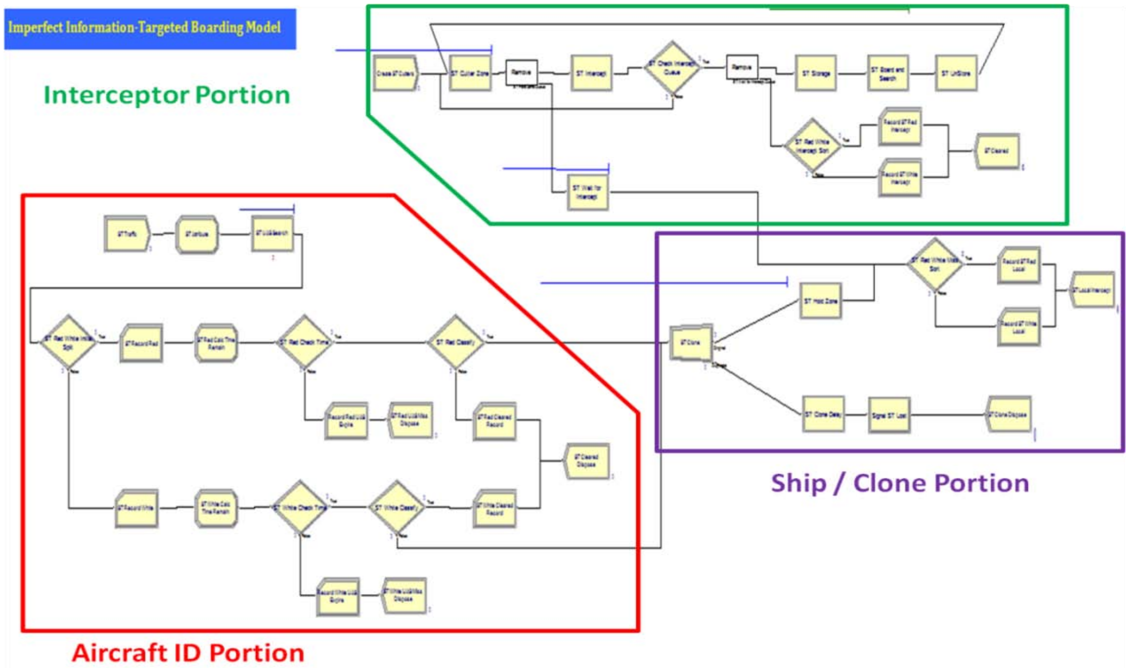

Figure 30 The Imperfect Information-Targeted Boarding Arena Simulation Screenshot

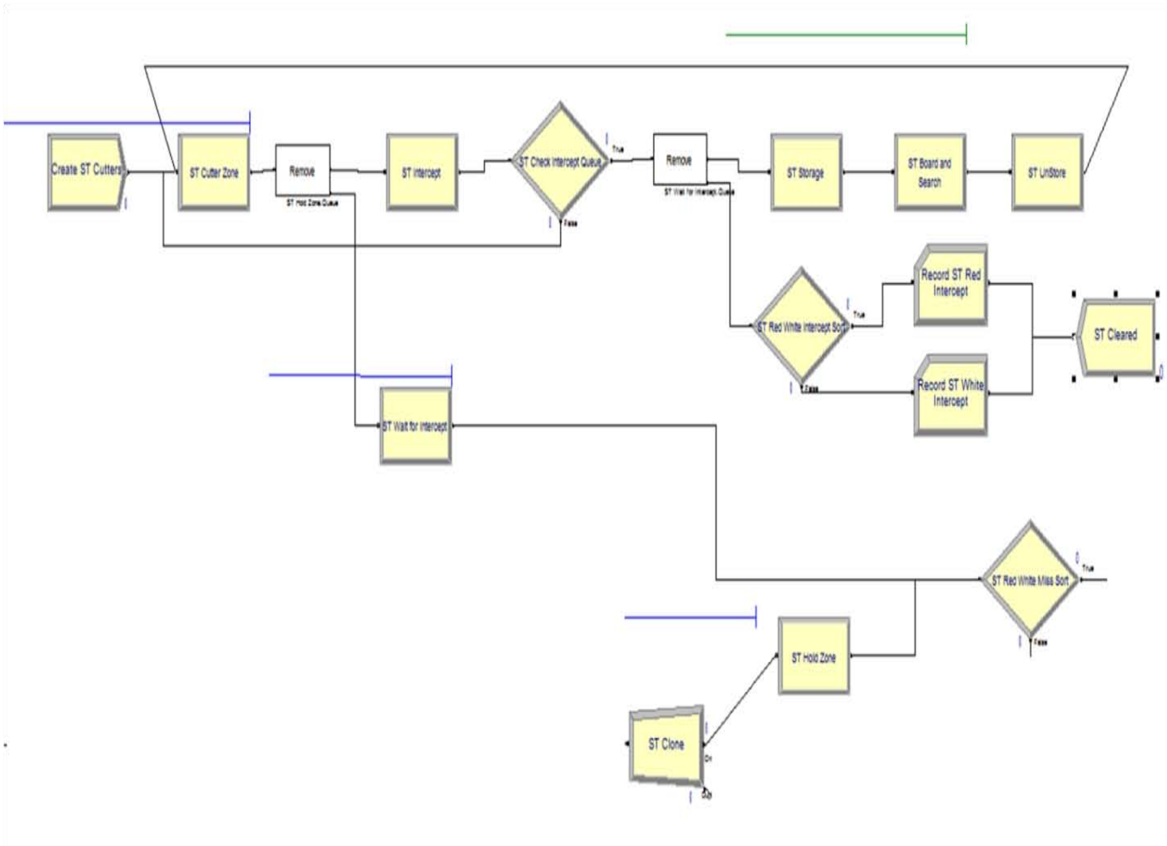

Figure 31 Arena Screenshot of Interceptor Portion of Imperfect Information-Targeted Boarding Scenario

The Interceptor portion of this scenario is similar to the Good Information-Targeted Boarding scenario. The interceptors are created in the *Create ST Cutters* module on the upper left. The interceptors wait in the next module, *ST Cutter Zone*, for a ship to arrive in the *ST Hold Zone* module on the lower right. When a ship is waiting for boarding and an interceptor is available, the interceptor activates the first *Remove* module and removes the ship from the *ST Hold Zone* and places the ship in the *ST Wait for Intercept* module in the middle section. The interceptor is delayed for random time while it is in the *ST Intercept* module; this simulates the time for the interceptor to transit to the ship. In the next diamond shaped module, *ST Check Intercept Queue*, the interceptor confirms the ship has not left the zone, and if available processes the ship for boarding. The ship is sorted either Red or White based on previously assigned attribute and counted in the four modules in the middle past the second *Remove* module; this sorting is count

how many actual white ships were misclassified and boarded by interceptors. The interceptor is delayed for the random boarding time and returns to the *ST Cutter Zone* module when available to intercept and board another ship or it removes the first ship in the queue if a ship(s) is already waiting.

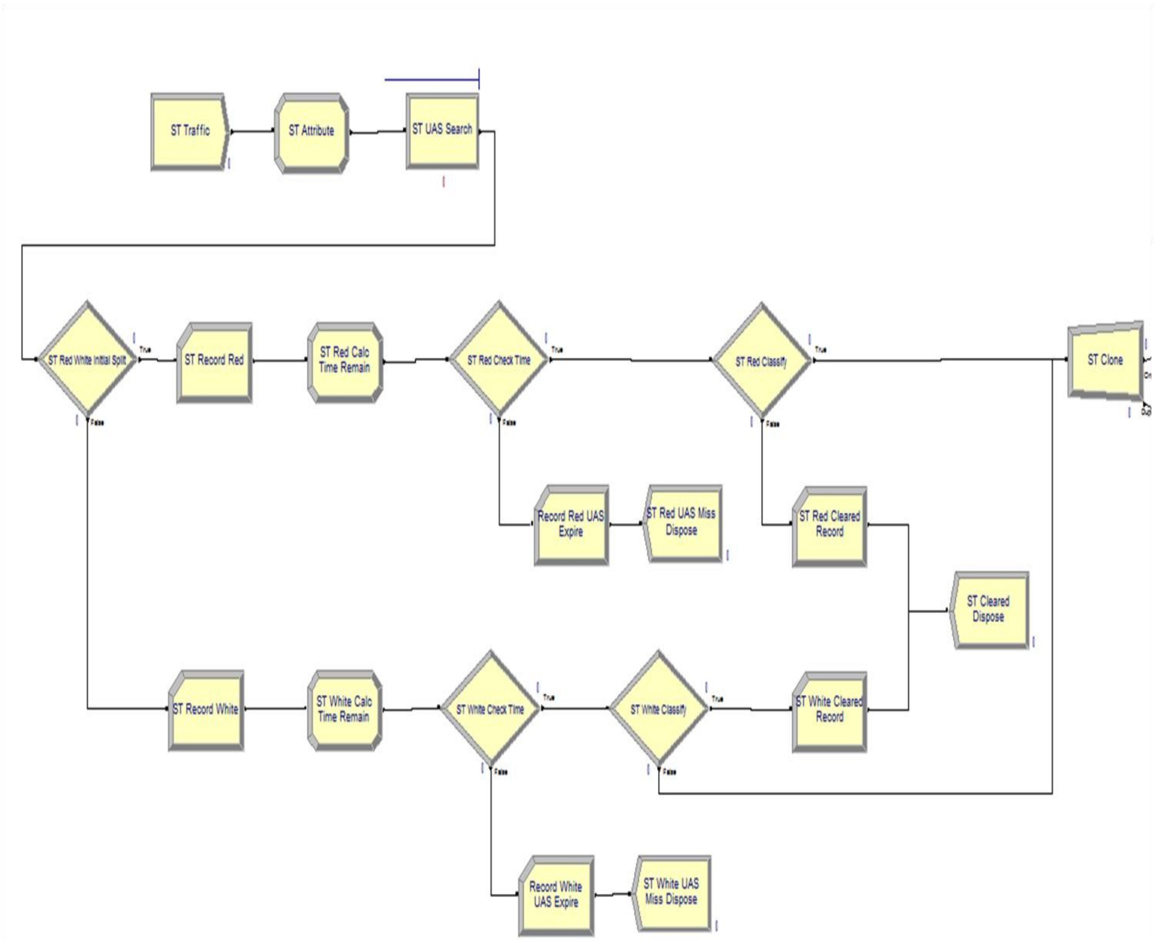

Figure 32 Arena Screenshot of Aircraft ID Portion of Imperfect Information-Targeted Boarding Scenario

The Aircraft ID portion of the Arena model is the section that creates and labels each ship with correct classification. First ships are created in the upper left module, *ST Traffic,* and assigned specific attributes including a unique serial number in the next module, *ST Attributes*. Next, the ship is delayed a random time in the *ST UAS Search* module to represent the time an aircraft takes to travel to and classify the track. Next, the ship moves through the diamond module, *ST Red White Initial Split,* where the ship

assigned either an actual Red or White classification based on the target percentage input and a random number draw. The numbers of Red or White ships are counted and the remaining time in zone for the ship is calculated in the next two modules from both paths leading from the *ST Red White Initial Split* module. The next diamond modules check the ship's time remaining and counts the ships that have left the region. The next diamond module on both paths is the conditional probability calculation. Using the user defined conditional probability the Red and White ships are classified either Red or White. From here White ships classified White are counted and disposed, while Red ships classified White are also counted and cleared. The red and white ships classified red move to the *ST Clone* module for the next portion. The ships move instantaneously through all modules in this section except for the *ST UAS Search* module at the start.

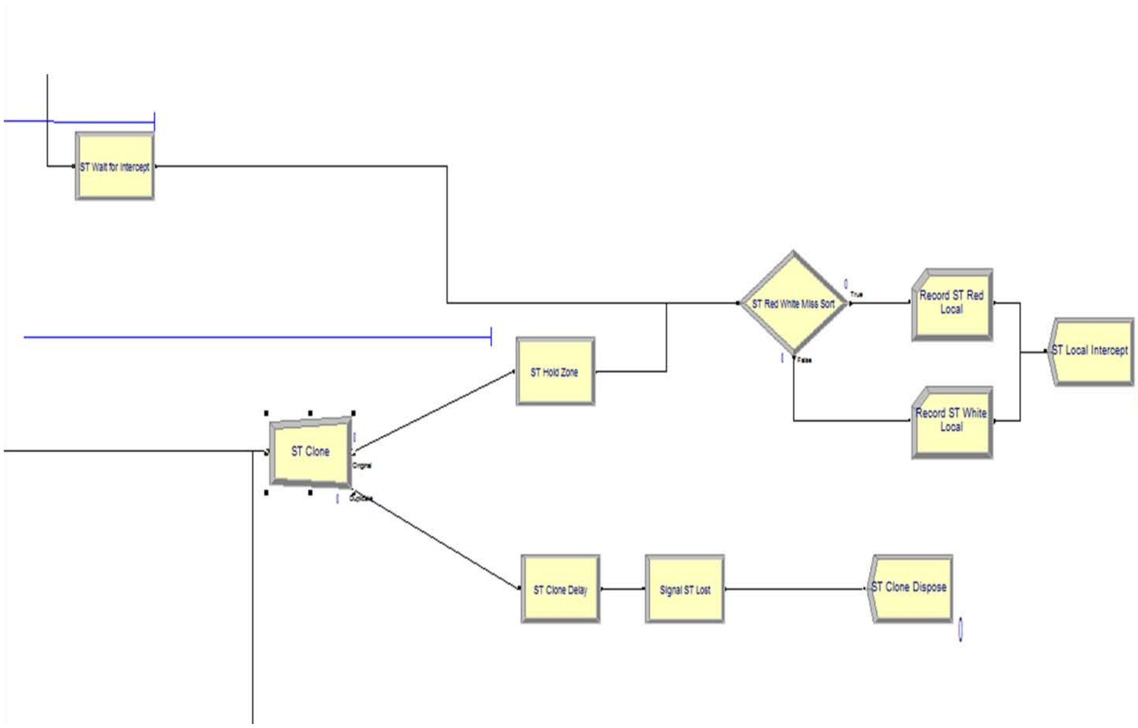

Figure 33 Arena Screenshot of Ship/Clone Portion of Imperfect Information-Targeted Boarding Scenario

The Ship/ Clone portion starts with *ST Clone* module in the lower left, which continues from the Aircraft ID portion. The ships classified Red are cloned and the actual ship moves to the *ST Hold Zone* module where it waits for an interceptor to become

available or a signal from its clone that its time in zone has expired. The ship's clone moves to the *ST Clone Delay* module where it waits until the ship time in zone assigned variable expires. When the clone's time expires, it moves to the *Signal ST Lost* module where it sends a unique signal based on the serial number assigned when the ship is created, to the actual ship to leave the zone. If the actual ship is in the *ST Hold Zone* module or *ST Wait for Intercept* module the clone's signal releases it from the queue where it moves the diamond shaped *ST Red White/ Miss Sort*. The actual ship is sorted by type (red or white) and counted for the respective MOE. After the clone sends its signal it is disposed, and if the actual ship has already completed the boarding process the clone signal does not affect other ships due to the unique serial number of each ship and clone.

These portions describe the Imperfect Information-Targeted Boarding Simulation, which includes aircraft and MOTR assets. The model's key MOE is Miss Rate or the fraction of ships in the target set not intercepted by MOTR assets, but other data can be collected including average delay at the interceptor queue, and the average number of interceptors in the queue. The Miss Rate only considered target set ships that have entered and left, by boarding or clone signal, the simulation for the scenario time or only target ship entities that have reached the dispose modules are counted.

Input	**Description**
Arrival Rates	Time between Arrivals to the Port
Board and Search Time	Time to Board and Search a Vessel
Ship Time in Zone	Time a Ship is available for Boarding and Search
Aircraft Search Time	Time for an Aircraft to find and Classify a Ship
Target Percentage	Percentage of Total Traffic that is Red
Crr	Conditional Probability a Red Ship is Classified Red
Cww	Conditional Probability a White Ship is Classified White

Table 40 Imperfect Information-Targeted Boarding Input Parameters for Arena Simulation

APPENDIX C.

A. INPUT PARAMETER CHARACTERIZATION

For the analytical and simulation models built, three input random times were characterized by parametric distributions from data output from a smaller JAVA based simulation. The three model input parametric distributions are for ship time in zone, undirected searching aircraft ship detection times, and directed search aircraft detection times. This appendix describes the smaller simulations and data analysis techniques in detail to obtain the parameterized distributions used in Chapters III, IV, and V.

B. SHIP TIME IN ZONE ESTIMATION

To estimate the parameters for the distribution of the time a ship is subject to detection and search a small simulation is built to mimic the operational movement of the ships across the area of operations. To obtain a reasonable sized sample, 1000 ship tracks are randomly generated. The ships travel in a 200 nm by 100 nm rectangle starting at the left side and ending on the right side with a constant speed drawn from a uniform distribution between 15 and 30 knots. The time each ship takes to reach the other side of the box is recorded as the output of the model. The ship's destination point on the right side of the box is located more towards the center of the right side of the box to simulate a convergence at the port's Traffic Separation Scheme or Entrance Channel. The ship's destination is drawn from a Normal distribution with mean equal to the center of the right side and a standard deviation of 10 miles; this distribution forces traffic towards the center. The ship's initial starting position is drawn from a Uniform distribution between the top and bottom of the left side, and each ship starts from the left side. It is assumed that all ships travel independently of each other; the initial ship position, the ship's destination and the ship's speed are independent random variables. The time a ship spends in the region is simulated. Using these generated times; parameters for a Beta, Gamma, Normal, and Exponential distribution are estimated using Method of Moments or Maximum Likelihood Estimators method.

The Beta distribution parameters were estimated using the Method of Moments Estimators described in National Institute of Standard and Technology's Engineering Statistics Handbook (National Institute of Standards and Technology, 2006). The Beta distribution parameters are listed below in Table 6. The sample data is adjusted by the method so all data points fall between zero and one. Figure 34 is simulation data and the parameterized distribution plotted in a QQ-plot using the S-Plus Statistical Package (Insightful Corporation, 2007). The Beta distribution provides the best fit of the data when compared to the QQ-plots of the other parameterized distribution based on the data.

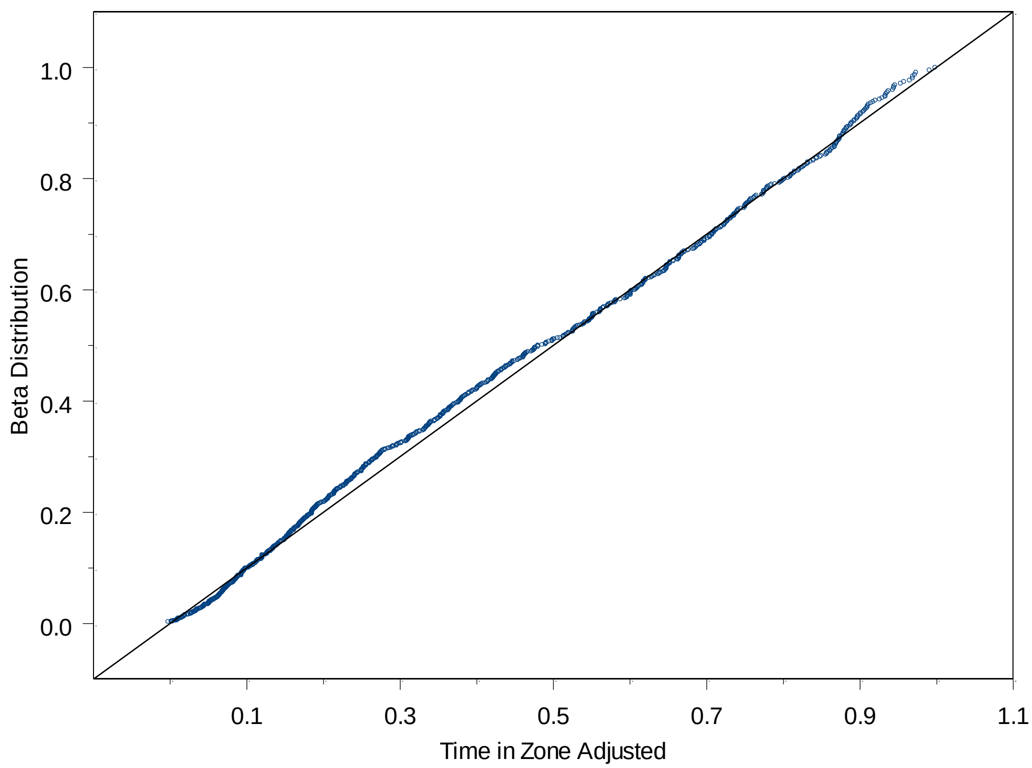

Figure 34 Ship Time in Zone Data with estimated Beta Distribution QQ-plot

The Gamma distribution parameters were estimated by using the Method of Moments Estimators described in National Institute of Standard and Technology's Engineering Statistics Handbook (National Institute of Standards and Technology, 2006). The final parameters for the distribution are displayed below in Table 6. The sample data is adjusted by the method so minimum data points falls at zero. Figure 35 is simulation data and the estimated distribution plotted in a QQ-plot using the S-Plus Statistical

Package (Insightful Corporation, 2007). The Gamma distribution provides a fair estimation of the simulation data but the sample diverges from the estimated distribution along the right tail.

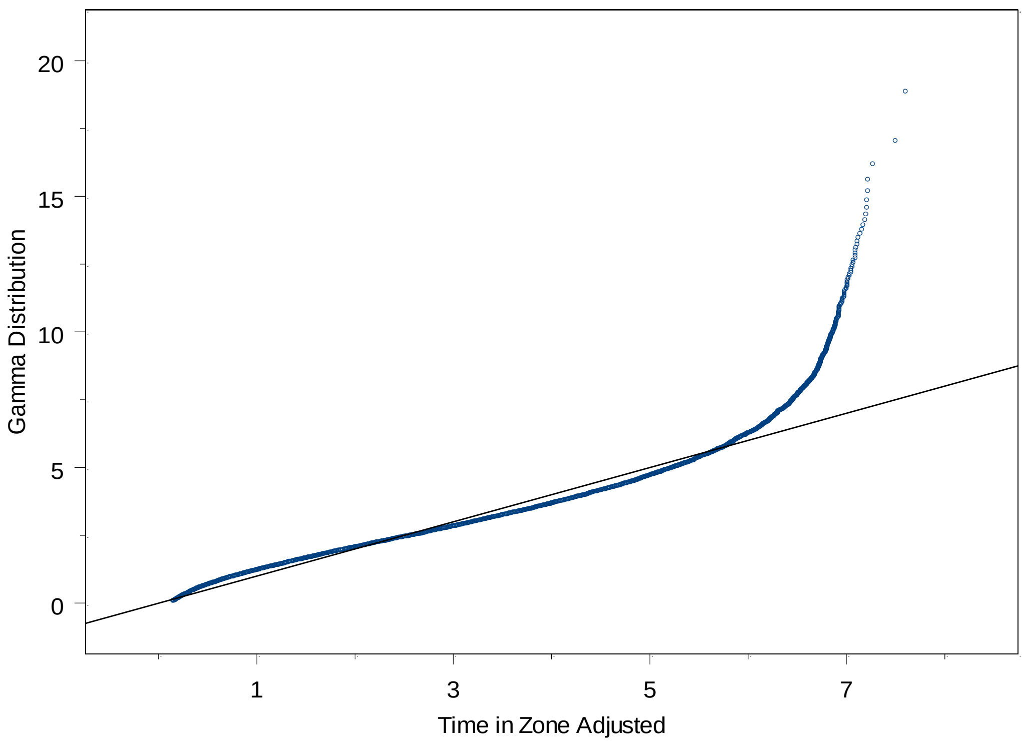

Figure 35 Ship Time in Zone Data with estimated Gamma Distribution QQ-plot

The Normal distribution parameters were estimated by using the Maximum Likelihood Estimators described in *Probability and Statistics* (Devore, 2008). The final parameters for the distribution are displayed below in Table 6. Figure 36 is the simulation data and the estimated distribution plotted in a QQ-plot using the S-Plus Statistical Package (Insightful Corporation, 2007). The Normal distribution provides an estimation of the simulation data with divergence from the sample at both tails.

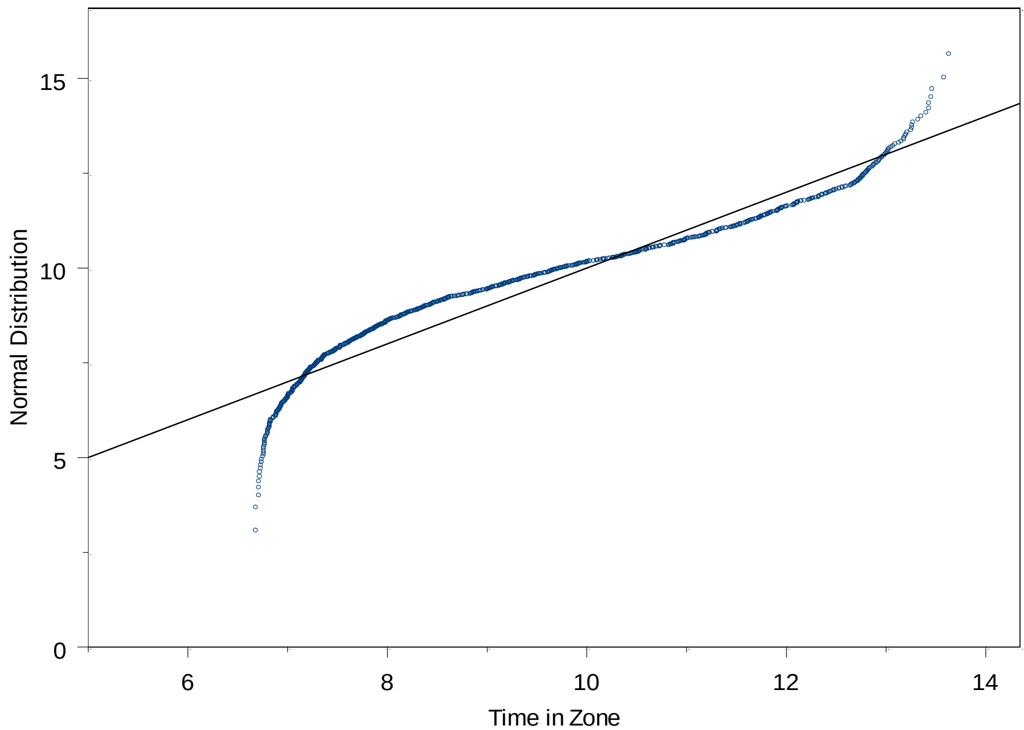

Figure 36 Ship Time in Zone Data with estimated Normal Distribution QQ-plot

The Exponential distribution parameter was estimated by using the Maximum Likelihood Estimators described in *Probability and Statistics* (Devore, 2008). The final parameter for the distribution is displayed below in Table 6. Figure 37 is the simulation data and the estimated distribution plotted in a QQ-plot using the S-Plus Statistical Package (Insightful Corporation, 2007). The Exponential distribution provides an estimation of the simulation data with significant divergence at the right tail.

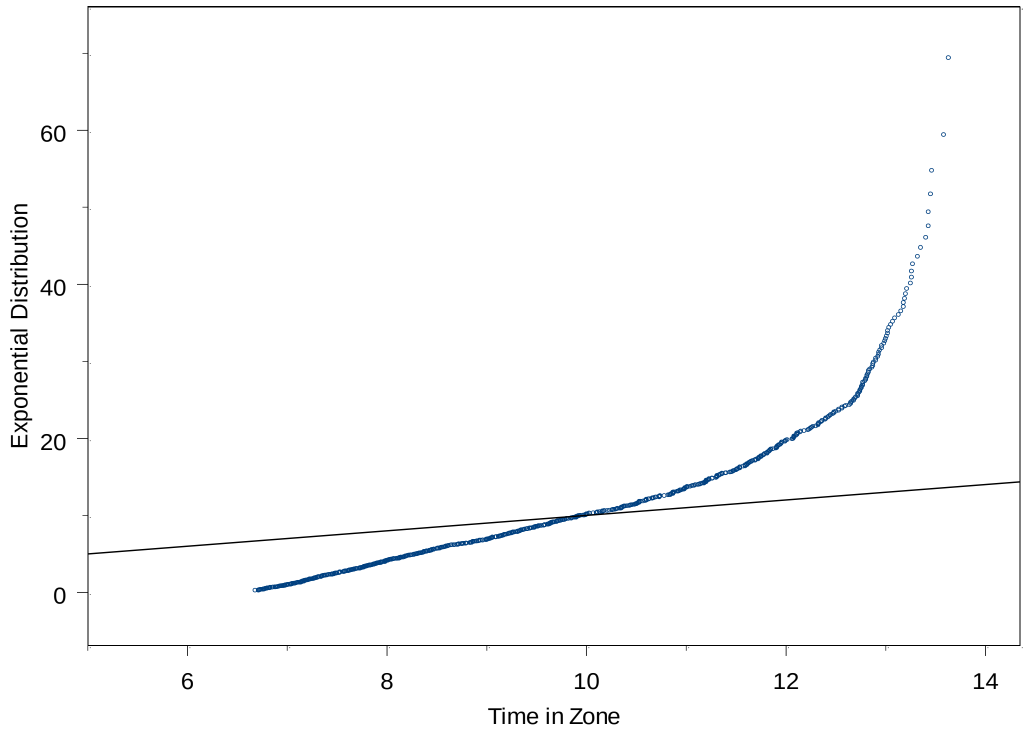

Figure 37 Ship Time in Zone Data with estimated Exponential Distribution QQ-plot

The four distributions chosen are distributions that the Arena Software package can replicate for the simulation runs. The Exponential distribution is estimated to perform analytical and simulation model comparisons in Chapter IV. The individual parameters of the different distributions are displayed in Table 41.

Distribution	Parameters	Equation
Beta $f(x;\alpha,\beta)=\frac{x^{\alpha-1}(1-x)^{\beta-1}}{B(\alpha,\beta)}$ $X=(h-l)*x+l$	$\alpha=0.79$ $\beta=1.31$ $h=13.65$ $l=6.70$	$6.70+6.95*Beta(\alpha,\beta)$
Gamma $f(x;\alpha,\beta)=\frac{1}{\beta^{\alpha}\Gamma(\alpha)}x^{\alpha-1}e^{-\frac{x}{\beta}}$	$\alpha=1.84$ $\beta=1.55$	$6.70+Gamma(\alpha,\beta)$
Normal $f(x;\mu,\sigma)=\frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{(x-\mu)^2}{(2\sigma)^2}}$	$\mu=9.31$ $\sigma=1.91$	-
Exponential $f(x;\lambda)=\lambda e^{-\lambda x}$	$\lambda=0.11$	-

Table 41 Ship Time in Zone Distribution Parameters

C. UNDIRECTED SEARCHING AIRCRAFT ESTIMATION

To estimate the parameters for the distribution of ship detection time for undirected searching aircraft distribution a JAVA based simulation is built to mimic the operational movement of the ships and searching aircraft across the area of operations.

First, to obtain reasonable sized samples of ships crossing the area, 1000 ship tracks are randomly generated and placed in bins to ensure equal spacing across the region. The bins were 10 equal spaced upper and lower bounds along the North-South axis with each bin area covering 10 nm on the left side of the rectangle with 100 ship tracks starting in each bin. The bins are numbered from North to South, so that Bin one’s North-South Coordinates are between 90 and 100. The ships travel in a 200 nm by 100 nm rectangle starting at the left side and ending on the right side with a constant speed

drawn from a uniform distribution between 15 and 30 knots. The ship's destination point on the right side of the box is located more towards the center of the right side of the box to simulate a convergence at the port's Traffic Separation Scheme or Entrance Channel. The ship's destination is drawn from a Normal distribution with mean equal to the center of the right side and a standard deviation of 10 miles; this distribution forces traffic towards the center. The ship's initial starting position is drawn from a Uniform distribution between the top and bottom of it respective bin on the left side, and each ship starts from the left side. It is assumed that all ships travel independently of each other; the initial ship position, the ship's destination and the ship's speed are independent random variables. For the undirected search aircraft simulation, each ship's North South starting coordinate was selected from a bin of to ensure that all positions along the North-South axis were represented.

Using the bin ship tracks, a variable number of aircraft are positioned in non-overlapping search boxes within area of operations. The boxes are of equal size so two aircraft split the area in half, three aircraft in thirds, four aircraft into fourths, etc. The graphical diagram for ship and four searching aircraft is displayed in Figure 38. The simulation output is the time when the ship is within 5 nm of the aircraft or when the ship leaves the area; whether or not the ship leaves the area prior to detection is recorded as a binary variable. The aircraft search pattern is chosen as a primarily in a North-South direction, after the simulation times were compared to aircraft with primarily an East-West search pattern. The simulation output creates right censored data for the aircraft search times.

Using the simulation data and the random censoring model parameter for Weibull distribution are estimated using maximum likelihood estimate (Crowder, Smith, & Sweeting, 1991). The resulting estimated parameters for a Weibull distribution based on the bin and the number of aircraft are displayed in Table 42. The Mean and Standard Error of the estimated Weibull distribution for the number of searching aircraft and targets leaving from specific bins is displayed in Table 43. The summary of estimated Weibull parameters for the entire data set (all bins combined) compared to each individual bin average is displayed in Table 44. The estimated parameters for the entire

data set without the bins are reasonable approximation to the estimates of the Weibull parameters by bin. For the Weibull distribution used in the chapters, the estimated parameters of the entire 1000 tracks are used instead of the individual bin estimated parameters. The final Weibull distribution parameters with the distributional form are displayed in Table 45.

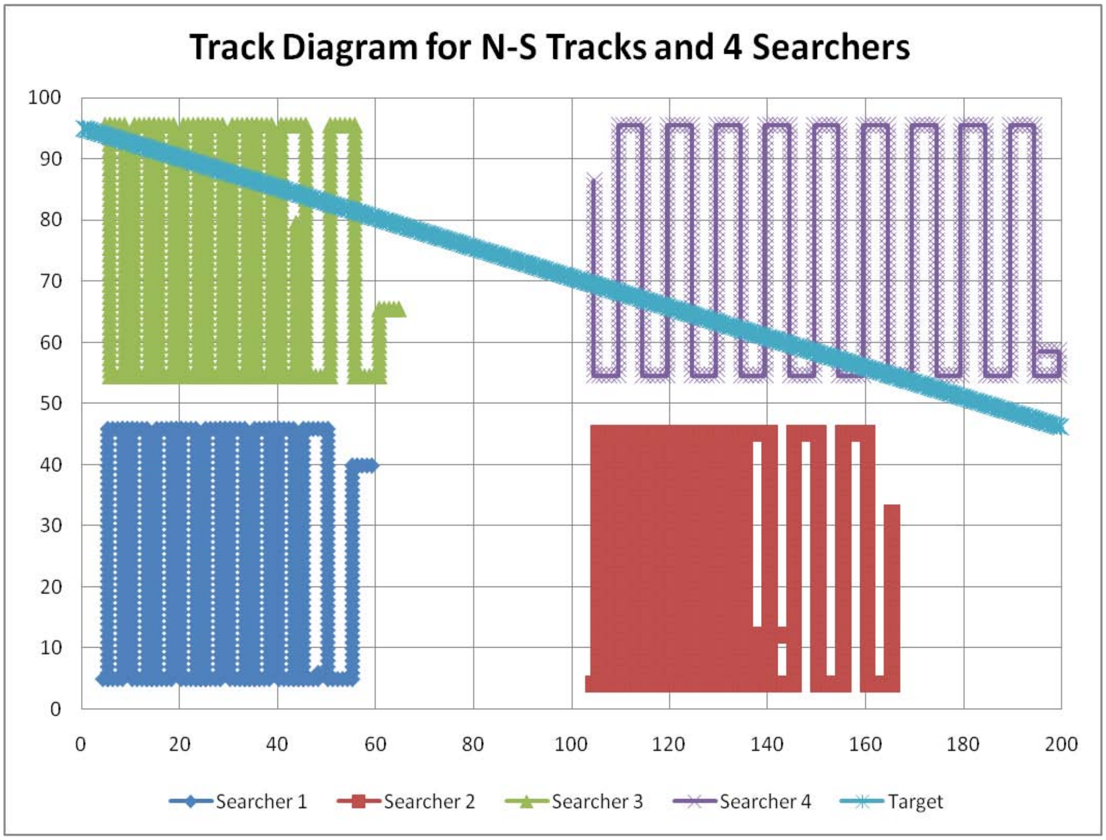

Figure 38 Graphical Depiction of Undirected Searching Aircraft Search Pattern and Search Boxes in the JAVA simulation

Weibull Shape Parameter							Weibull Scale Parameter					
Number of Aircraft							Number of Aircraft					
Bin	**1**	**2**	**3**	**4**	**6**		**Bin**	**1**	**2**	**3**	**4**	**6**
1	1.723	1.110	1.170	1.012	1.232		**1**	0.077	0.143	0.177	0.248	0.318
2	1.409	1.222	1.265	1.097	1.038		**2**	0.080	0.144	0.229	0.243	0.386
3	0.959	1.094	1.228	1.259	1.118		**3**	0.069	0.168	0.262	0.222	0.466
4	1.279	1.035	1.024	1.090	1.148		**4**	0.095	0.179	0.227	0.303	0.369
5	1.350	0.981	0.993	1.135	0.997		**5**	0.102	0.165	0.265	0.201	0.318
6	1.120	1.261	1.100	1.082	1.085		**6**	0.091	0.183	0.208	0.207	0.366
7	1.054	1.043	1.036	1.106	1.078		**7**	0.076	0.165	0.238	0.221	0.400
8	1.328	1.152	1.177	1.261	1.230		**8**	0.089	0.124	0.245	0.198	0.376
9	1.260	1.071	1.078	1.227	1.119		**9**	0.089	0.155	0.194	0.282	0.392
10	1.186	1.067	1.085	1.162	1.109		**10**	0.075	0.135	0.233	0.263	0.429
AVG	**1.267**	**1.104**	**1.116**	**1.143**	**1.115**		**AVG**	**0.084**	**0.156**	**0.228**	**0.239**	**0.382**

Table 42 Estimated Parameters of Weibull Distribution for Undirected Searching Aircraft Search Time by Bin

Weibull Bin Mean and Standard Error Comparison										
	Number of Aircraft									
	1		**2**		**3**		**4**		**6**	
Bin	**Mean**	**Std Error**	**Mean**	**Std Error**	**Mean**	**Std Error**	**Mean**	**Std Error**	**Mean**	**Std Error**
1	11.55	0.24	6.73	0.48	5.34	0.38	4.00	0.29	2.94	0.21
2	11.34	0.26	6.50	0.46	4.52	0.28	3.98	0.28	2.55	0.18
3	14.76	0.36	5.76	0.41	3.57	0.25	4.18	0.29	2.06	0.15
4	9.76	0.22	5.50	0.39	4.36	0.31	3.20	0.23	2.58	0.18
5	9.03	0.20	6.11	0.44	3.78	0.27	4.76	0.34	3.15	0.23
6	10.52	0.24	5.08	0.35	4.64	0.33	4.70	0.33	2.65	0.19
7	12.95	0.31	5.98	0.42	4.14	0.29	4.36	0.31	2.43	0.17
8	10.38	0.23	7.70	0.55	3.86	0.27	4.69	0.33	2.48	0.17
9	10.45	0.24	6.27	0.45	5.00	0.36	3.32	0.24	2.45	0.17
10	12.52	0.30	7.24	0.52	4.16	0.29	3.60	0.27	2.24	0.16
Bin Avg	11.33	0.26	6.29	0.45	4.34	0.30	4.08	0.29	2.55	0.18
Comp Data	11.37	0.27	6.23	0.14	4.27	.09	3.65	0.08	2.33	0.05

Table 43 Comparison of Means and Standard Errors of Estimated of Weibull Distribution for Undirected Searching Aircraft Search Time for Bins and Combined Data

Weibull Parameter Estimation Summary												
Number of Aircraft							Number of Aircraft					
	1	**2**	**3**	**4**	**6**			**1**	**2**	**3**	**4**	**6**
Comp Data	1.214	1.089	1.125	1.126	1.101		**Comp Data**	0.084	0.154	0.239	0.236	0.379
Bin AVG	1.267	1.104	1.116	1.143	1.115		**Bin AVG**	0.084	0.156	0.228	0.239	0.382

Table 44 Summary of Estimated Weibull Parameters for Undirected Searching Aircraft

Number of Searching Aircraft *Weibull* Distribution PDF $f(x;\lambda,k)=k\lambda\left(x\lambda\right)^{k-1}e^{-(x\lambda)^k}$	**Weibull Parameters** *Weibull* Parameters ($\lambda = Scale$ k=Shape) Characterization ($\mu = Mean$ σ=Standard Deviation)
1	$\lambda = 11.9$ k=1.2 $\mu = 11.2$ σ=9.3
2	$\lambda = 6.4$ k=1.1 $\mu = 6.3$ σ=5.8
3	$\lambda = 4.2$ k=1.1 $\mu = 4.0$ σ=3.6
4	$\lambda = 4.2$ k=1.1 $\mu = 4.0$ σ=3.6
6	$\lambda = 2.6$ k=1.1 $\mu = 2.5$ σ=2.3

Table 45 Final Continuous Searching Parameters for the Weibull Distribution

D. DIRECTED AIRCRAFT ESTIMATION

To estimate the parameters of a distribution for the time a directed aircraft moves between targets, a ship sent across the area until it is found by the aircraft. A JAVA based simulation is built to mimic the operational movement of the ships and directed aircraft across the area of operations.

The simulation uses a single ship and aircraft replicated 1000 times to obtain a reasonable sample of times between detections from a directed aircraft. The area of operations is a 200 nm by 100 nm rectangle. A ships position is randomly drawn from a uniform distribution for both the North-South and East-West Coordinate. The ship's destination point on the right side of the box is located more towards the center of the right side of the box to simulate a convergence at the port's Traffic Separation Scheme or Entrance Channel. The ship's destination is drawn from a Normal distribution with mean equal to the center of the right side and a standard deviation of 10 miles; this distribution

forces traffic towards the center. The Aircraft's position is randomly drawn from the Uniform distribution over the entire area of operations for both the North-South and East-West coordinate. As the simulation runs, if the ship enters an expanding circle around the aircraft the ship is detected and the time is recorded for output. The circle expands at 100kts based on the speed of the aircraft and at time zero, the circle is 5 nm in radius to represent the visual sweep width of the sensor. Only times when the ship is detected by the aircraft are considered for the estimation of distribution parameters; censored observation were discarded. The censored observation were less than one percent of total runs and are not considered since operators directing the aircraft would not send the aircraft on intercepts that are not possible. This simulation provides optimistic times since the optimal time of detection is recorded. Using these generated times parameters for a Uniform and Exponential distributions are estimated using Method of Moments or Maximum Likelihood Estimators method. A Normal and Gamma distribution were also estimated, but neither was tested in this thesis based on the QQ plots of the estimated parameters.

The Uniform distribution parameters were estimated by using the Maximum Likelihood method described in National Institute of Standard and Technology's Engineering Statistics Handbook (National Institute of Standards and Technology, 2006). The final parameters for the distribution are displayed below in Table 46. Figure 39 is the simulation data and the estimated distribution plotted in a QQ-plot using the S-Plus Statistical Package (Insightful Corporation, 2007). The Uniform distribution provides the best fit for the simulation data.

The mean of the estimated uniform distribution is comparable to analytical formula developed in Brahim and Gaboun, which calculated the average distance between two random uniform points in a rectangle (Brahim Gaboune, 1993). The analytical model result is 0.89 hours compared to the estimated uniform mean of 0.925 with standard deviation of 0.29.

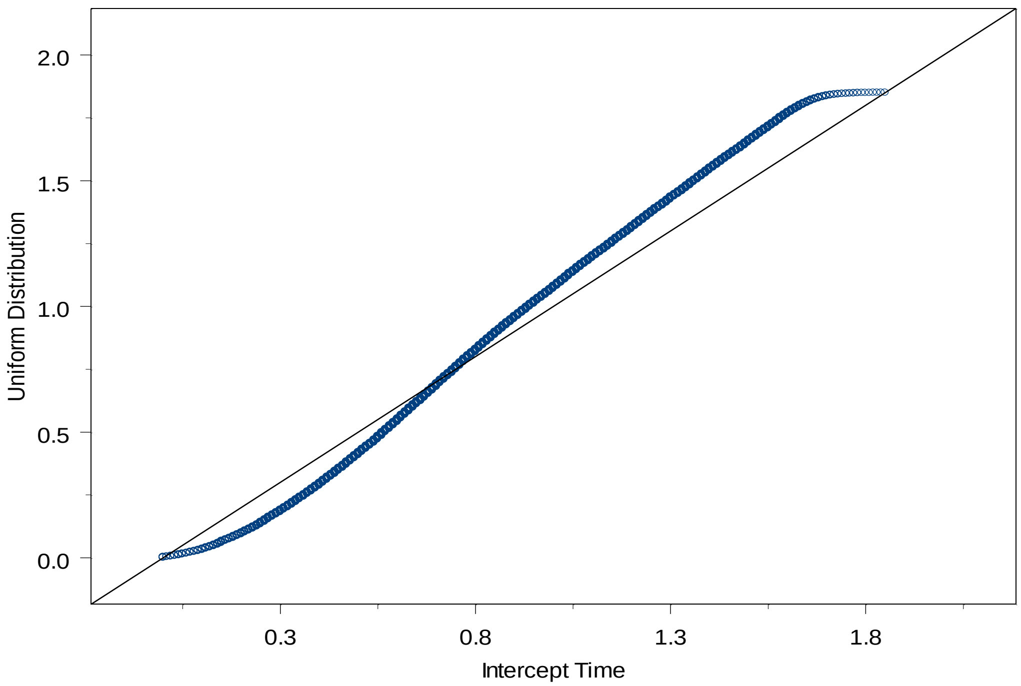

Figure 39 Directed Aircraft Search Time estimated Uniform Distribution QQ-plot

The Exponential distribution parameter for the directed aircraft search times was estimated by using the Maximum Likelihood Estimators described in *Probability and Statistics* (Devore, 2008). The final parameter for the distribution is displayed below in Table 46. Figure 40 is the simulation data and the estimated distribution plotted in a QQ-plot using the S-Plus Statistical Package (Insightful Corporation, 2007). The Exponential distribution provides an estimation of the simulation data with significant divergence at the right tail.

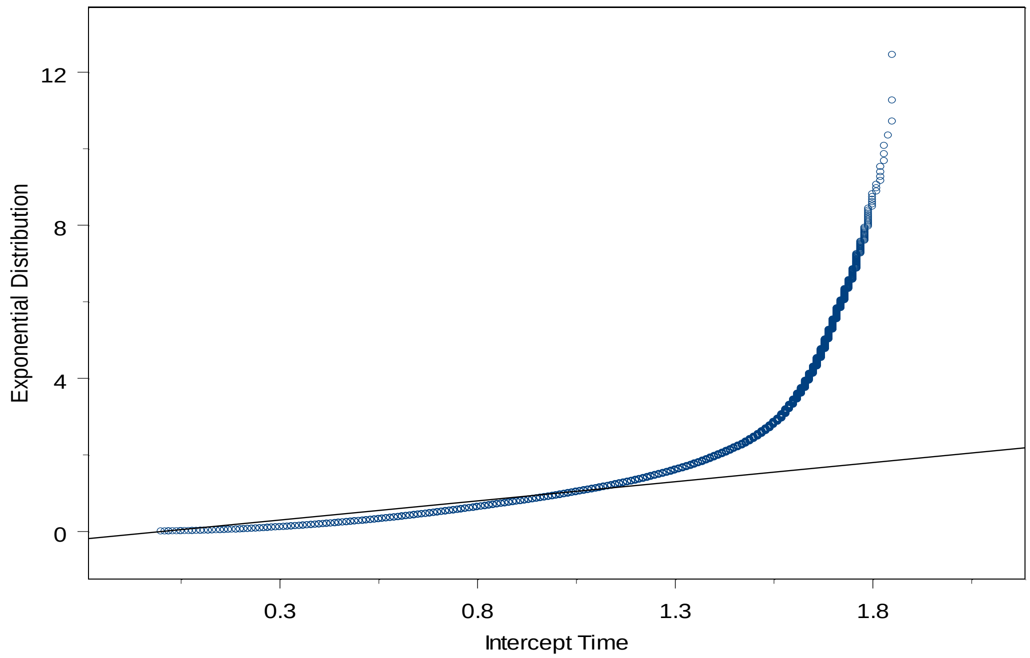

Figure 40 Directed Aircraft Search Time estimated Exponential Distribution QQ-plot

Both distributions are used in sensitivity of input distribution in Chapter III and the analytical and simulation models in Chapter IV. The final parameters of the estimated distributions are listed below in Table 46.

Distribution	**Parameters**
Uniform $f(x) = \frac{1}{b-a} \quad \text{for } a \le x \le b$	$a = 0$ $b = 1.85$
Exponential $f(x;\lambda) = \lambda e^{-\lambda x}$	$\lambda = 0.93$

Table 46 Directed Aircraft Search Time Distribution Parameters

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